Gaining Steam: Technology Diffusion with Recurring Lock-in

Richard Hornbeck
University of Chicago

Shanon Hsuan-Ming Hsu
Harvard University; NTU

Anders Humlum
University of Chicago

Martin Rotemberg
New York University

September 2025

Abstract

We examine barriers to technology adoption, drawing on the diffusion of steam power in US mills. Improvements in steam power generated greater relative growth in counties with less waterpower potential. Steam adoption was largely driven by entrants, with limited incumbent switching. Switching barriers continued to slow technology diffusion, despite entry and exit, because many smaller entrants opened with waterpower and then themselves became locked-in incumbents. We estimate a dynamic model of entry and technology adoption to quantify the delay in aggregate technology diffusion from this "recurring lock-in," and corresponding losses in aggregate efficiency due to positive externalities in technology adoption.

For helpful comments and suggestions, we thank the editor and referees along with many colleagues and seminar participants at Barcelona, BU, Columbia, the Business History Conference, CAED, the Cliometric Conference, Copenhagen, Dartmouth the EGC & IGC Firms, Trade, and Development Conference, George Mason, Harvard, HEC Paris, Hitotsubashi, the IGC STEG Annual Conference, LBS, Manchester, Manhattan College, Minneapolis Fed, the Mountain West Economic History Conference, NBER (EEE, EFG, and Productivity), NYU, NUS, Purdue, Oxford, Richmond Fed, SMU, UChicago, UCLA, USC, and Yale. We are grateful to: Jeremy Atack for sharing data and comments; to Sarah Armitage, Luise Eisfeld, Jeremy Majerovitz, and Jane Olmstead-Rumsey for conference discussions; to Sam Abers, Andrea Cerrato, Will Cockriel, Terence Chau, Bo-Yu Chen, Alison Doxey, Jiaxuan Lu, Ben Lualdi, Julius Luettge, Natalie Yang, and Vivian Zhang for their extensive research assistance; and to our data entry and processing teams at Digital Divide Data and the University of Chicago. This research was funded in part by the Initiative on Global Markets at the University of Chicago Booth School of Business, the Neubauer Family Faculty Fellowship, and the NBER Innovation Policy grant program. This material is based upon work supported by the National Science Foundation under Grant Number SES-1757050/1757051. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

Technological innovation drives economic growth, but the widespread adoption of new technology can be remarkably fast or slow (Strassmann, 1959; David, 1990; Comin and Hobijn, 2010). We examine the adoption of steam power, an iconic general purpose technology (Bresnahan and Trajtenberg, 1995; Jovanovic and Rousseau, 2005), which drove widespread industrialization and is a motivating example of "creative destruction" (Schumpeter, 1942; Hunter, 1985; Atack, Bateman and Margo, 2008). We examine the prolonged transition from water power to steam power in lumber and flour milling, which were leading sectors for mechanical power-use in the 19th century United States.

A typical explanation for the slow diffusion of new technologies is that the initial incumbents are locked into the old technology, which then endures as a result of their continued survival (Devine, 1983; Chari and Hopenhayn, 1991; Atkeson and Kehoe, 2007). We show that even after initial incumbents exit, displaced by entrants, technology diffusion can be delayed by *recurring lock-in*. Entry is not a panacea for incumbent lock-in when the old and new technologies are horizontally differentiated, such that some entrants prefer the old technology. As successive generations of firms enter using the old technology, some survive and become new locked-in incumbents. These entrants regenerate technological lock-in. Using a quantitative model of firm entry and technology adoption, we show that establishment-level lock-in can delay aggregate adoption of some types of technologies long after the initial incumbents have closed. When firm adoption of the new technology generates positive externalities for other firms' technology adoption, this recurring lock-in causes aggregate inefficiency both along the transition path and in steady state.

Steam adoption in US milling provides an opportunity to explore firm-level dynamics over a long time horizon. Throughout our sample period, US milling was highly dynamic with substantial entry and exit. Smaller mills often entered using water power because of steam's relatively high fixed costs. These waterpowered entrants then faced switching barriers from their sunk investments in water power because they faced an opportunity cost from scrapping a functional power source. Each generation of entrants adopted steam at higher rates, as steam power improved, but initially-small mills often continued to enter using water power and perpetuated a cycle of lock-in. By contrast, we show that firm entry would have generated much faster technological diffusion, without recurring lock-in from switching barriers, if the new technology had been relatively beneficial to smaller firms.

To motivate the empirical analysis, we begin with a stylized dynamic model of recurring lock-in, in the spirit of Hopenhayn (1992) and Bustos (2011). In the presence of lock-in, historical disadvantages can be dynamic technological advantages. In places where the old technology is less feasible, there are fewer locked-in firms and the new technology is more rapidly adopted, accelerating output growth.

A key advantage of our empirical setting is that we can explore these predicted dynamic patterns by exploiting geographic variation in counties' waterpower potential, which generated substantial variation in the costs of installing waterpower. Lumber and flour mills were broadly spread across the country due to high transportation costs and perishability of their finished products. Within locations, steam and waterpowered mills directly competed with each other because, other than their differences in power source, they used the same material inputs and produced the same goods. As a result, each county by industry captures different markets that were dependent on local geographic endowments for access to water power. We estimate that steam technology was less impactful in counties with greater waterpower potential, as both early-use and continued-use of water power created greater lock-in. In counties with less waterpower potential, milling adopted steam power more rapidly and output grew faster.

To measure plant-level technology use and switching, we digitize the complete surviving establishment-level manuscripts from the US Census of Manufactures in 1850, 1860, 1870, and 1880. We construct a balanced panel of 1199 county-industries (613 lumber-mill counties and 586 flour-mill counties), covering 689 unique counties and 80,000 establishment-year observations. We hand-link mills over time to create an establishment-level panel, which provides several motivating empirical patterns. Across decades, entrants were four times more likely to use steam power than incumbent water powered mills, even though larger incumbents were more predisposed to benefit from steam, and the incumbents who did switch to steam power grew quickly. Differences in entry patterns drove the cross-county growth differentials by waterpower potential.

While the reduced form results show that lock-in was important to incumbents, these results are unable to speak to whether plant-level barriers substantially delayed overall technology adoption and whether this created broader inefficiencies. Understanding the aggregate causes and consequences of technology diffusion requires modeling general equilibrium forces, with competition among entrants and incumbents in a market.

We develop and estimate a quantitative version of the stylized model, which we identify using our estimated differences by county waterpower potential and establishment-level patterns in water and steam usage. Heterogeneous firms make forward-looking decisions in each period about whether to enter, operate or exit, and which power technology to use. Water power purchase costs vary over space, with variation in local waterpower potential, whereas steam costs decline over time as the technology improves. Incumbents face technology switching barriers, including sunk investments in power technology. We simulate the transition path from 1830 to 1900, as steam technology improved, matching the targeted moments and non-targeted moments. We estimate a switching cost that is equal to roughly two months of revenue, with about 90% of this switching cost accounted for by sunk investment in water infrastructure that was physically attached to a mill and therefore difficult to resell.

Removing the switching costs, in counterfactual exercises, we find that these switching barriers substantially lowered the aggregate spread of the new technology – especially along the transition path. Only 2% of mills active in 1880 had existed in 1850, so the aggregate effects of switching barriers reflect their impact on younger incumbents. Throughout the period, many smaller and relatively less productive entrants were attracted to water power's lower fixed costs. These surviving entrants then became young locked-in incumbents, particularly if they became more productive and did not want to abandon their functional water infrastructure.

By contrast, we show that in a counterfactual environment where the new technology has lower fixed costs of production (and higher marginal costs), technology diffusion would be rapid even with the same switching barriers. This is because lower-productivity entrants would enter using the new technology and would not themselves become locked into the old technology as their productivity grew.

While incumbents benefited from the option value of steam, they faced increased competition from entrants. The switching barriers were sufficiently large that incumbent firms overall lost value from the introduction of steam power. Removing switching barriers would benefit incumbents, whose optimal power choice changes as steam power improves, but also increases aggregate sectoral output in steady state. This is because more firms enter the economy, benefiting from the option value of potentially seamlessly switching to steam power in the future.

Even though firms make privately-optimal forward-looking investments in their own power technology, recurring lock-in generates aggregate economic losses along the transition path and in steady state. The social inefficiency stems from early adopters of steam having local positive externalities on subsequent steam adoption, which we identify from the substantial aggregate output growth in lower waterpower potential counties that is larger than is explained by firms' internalized benefits from steam adoption. Earlier adoption of general purpose technologies, like steam, can increase the local knowledge base and thereby generate aggregate economic efficiency gains.

Our establishment-level analysis complements a literature studying long-run technology diffusion from a more aggregate perspective (Griliches, 1957; Jovanovic and Lach, 1989; Greenwood and Yorukoglu, 1997; Comin and Mestieri, 2014). We estimate large but not prohibitive barriers to switching, placing our results between common assumptions of either infinite switching costs (Chari and Hopenhayn, 1991; Collard-Wexler and De Loecker, 2015) or no lock-in (Basu and Weil, 1998; Acemoglu and Zilibotti, 2001; Greenwood, Seshadri and Yorukoglu, 2005; Benhabib, Perla and Tonetti, 2021; Miller et al., 2022). Our analysis is related to literature on "vintage capital" that considers the technology embedded in each successive generation of capital (Salter, 1960; Solow, 1962; Denison, 1964; Benhabib and Rustichini, 1991; Chari and Hopenhayn, 1991; Atkeson and Kehoe, 1999; Gilchrist and Williams, 2000; Jovanovic and Yatsenko, 2012; Caunedo and Keller, 2021), and a literature studying why incumbents are slow to adopt new technologies (Frankel, 1955; Saxonhouse and Wright, 1987; Jovanovic and MacDonald, 1994; Parente, 1994; Henderson, 1995; Jovanovic and Nyarko, 1996; Hall, 2004; Snow, 2004; Holmes, Levine and Schmitz Jr., 2012; Verhoogen, 2023). By contrast, we focus on the role of entry and emphasize the delay in technology adoption when *entrants* use the old technology (and then become locked-in incumbents). We estimate that the productivity of steam use is increasing in the local steam share, related to a literature studying how complementarities shape technology adoption (Buera et al., 2021; Alvarez et al., 2023; Crouzet, Gupta and Mezzanotti, 2023; Aghion et al., 2024; Buera and Trachter, 2024; Aghion et al., 2025). The most closely related model is from Humlum (2022), who studies robot adoption in modern firms but abstracts from entry decisions.

The importance of waterpower availability for power technology choices was understood historically (Montgomery, 1840), and occurs empirically across different contexts (Temin, 1966; Atack, 1979; Atack, Bateman and Weiss, 1980; Cooney, 1991; Bishop and Muñoz-Salinas, 2013; Chernoff, 2021; Ashraf et al., 2024; Guilfoos, 2025). Our contribution is using this geographic variation to identify how entry and switching impact technology diffusion, leveraging our newly-digitized full establishment-level Census of Manufactures to consider firm-level dynamics. Because waterpower potential comes from the interaction of water flow and elevation changes, we can exploit the robust effect of waterpower after controlling for the direct effects of water flow and terrain ruggedness (along with other local characteristics that might impact manufacturing activity). This dynamic influence of geographic endowments on firm technology adoption complements research on path dependence in technologies themselves, including railroad gauges (Veblen, 1915), keyboard layouts (David, 1985), light bulbs (Armitage, 2023), and telephone switchboards (Feigenbaum and Gross, 2024).

Steam power was a transformative technology because it reduced the dependence of manufacturing on local geography for mechanical power. Steam was adopted faster in places with less waterpower potential, partly due to static forces that raised the returns to steam power in those places. Dynamic forces also sustained initial investments in water power, through recurring lock-in, which created a technological drag from earlier geographic advantage. Faster steam adoption, entry, and output growth were amplified by agglomeration spillovers, and were more concentrated in lower waterpower counties where greater early adoption of steam power itself encouraged further adoption of steam power. Therefore, despite substantial firm entry and exit, technological lock-in can dampen social gains from new technologies over a long time horizon.

I A Stylized Model of Technology Choice with Recurring Lock-in

To highlight the influence of technology lock-in, we start with a three-period partial equilibrium model of technology choice and firm entry (following Hopenhayn (1992) and Bustos (2011)). The comparative statics also motivate which descriptive statistics and regression outcomes will be of particular interest in the establishment-level data. See Appendix D.1 for an explicit derivation of the model.

Firms use one of two rotational power technologies R: water (W) or steam (S). Steam power has a higher purchase price, but is associated with a lower marginal cost of production. In the initial first period steady state, water is the only available power technology. In the second period, steam is unexpectedly introduced. In the third period, the purchase price of steam declines as expected, and the economy reaches its final steady state.

In each period, firm j in county c and period t maximizes profits by choosing variable inputs x_{jct} and price p_{jct}, given its baseline productivity φ_j and chosen power technology R. Firms face a constant elasticity of demand, and produce using a constant returns to scale technology: $y_{jct} = \exp(\varphi_j + \gamma_R)x_{jct}$. Steam is associated with lower marginal costs ($\gamma_S > \gamma_W$) and a higher purchase price ($c(S) > c(W)$). Incumbent mills face an additional switching cost to change power technology ($c(W, S)$). Mills exit with an exogenous probability.

New potential millers are born in each period, with a fixed productivity φ_j drawn from a normal distribution. In each period t, firms' endogenous choice of power technology and production is determined by their productivity φ_j in comparison to a set of cutoff productivities $\bar{\varphi}_t^R$. Our main interest is in how switching costs change the relationship between productivity and technology choice for incumbents relative to entrants.

In period 1, all firms have to use water power. The least-productive millers do not find it profitable to pay the fixed cost of water power, so all operational firms have $\varphi_j \geq \bar{\varphi}_1^W$.

In period 2, Figure 1 shows the productivity cutoffs right after steam power arrives (Panel A). All firms, both entrants and incumbents, adopt steam power when they have sufficiently high productivity ($\varphi_j \geq \bar{\varphi}_2^S$). For mills with slightly lower productivity, $\bar{\varphi}_2^L \leq \varphi_j < \bar{\varphi}_2^S$, entrants adopt steam power while incumbents continue to use water power because of the switching cost. These incumbents are "locked-in," in the sense that they use water power because they were born in period 1, but they would have used steam power if they had been born in period 2. Entrants and incumbents both use water power when they have sufficiently low productivity ($\bar{\varphi}_2^W \leq \varphi_j < \bar{\varphi}_2^L$).

In period 3, as the cost of steam power falls, there is now "recurring lock-in." Some period 2 entrants, who would have started with steam, are locked into waterpower. Thus, even if most incumbents from period 1 have exited by period 3, there is a new wave of firms that entered in period 2 and are now locked into the old technology.

Figure 1 illustrates the five distinct productivity regions for technology choices, as a function of firm productivity. The most productive firms, in region V (above $\bar{\varphi}_2^S$), use steam power whenever available (periods 2 and 3). In region IV (between $\bar{\varphi}_3^S$ and $\bar{\varphi}_2^S$), water-powered incumbents switch to steam power in period 3, whereas entrants in this productivity region enter using steam power in both periods. In region III (between $\bar{\varphi}_2^L$ and $\bar{\varphi}_3^S$), water-powered incumbents remain locked-in to water power, whereas entrants in both periods 2 and 3 continue to start with steam power. In region II (between $\bar{\varphi}_3^L$ and $\bar{\varphi}_2^L$), period 3 entrants use steam power, but period 2 entrants use water, and in both periods water-powered incumbents do not switch. Finally, in region I (between $\bar{\varphi}_2^W$ and $\bar{\varphi}_3^L$), all mills use water power and never adopt steam.

Region II highlights "recurring lock-in," in which moderately-productive entrants in period 2 are drawn to the old technology upon entry and are locked-in to water power in period 3 when the cost of steam declines. While the initial incumbent mills in period 1 did not anticipate the arrival of steam, recurring lock-in occurs even as the entrants make dynamically optimal and fully informed power choices.

Figure 2 shows the corresponding steam adoption shares, which will be a key empirical moment. Panel A shows that a higher share of entrants adopt steam power than water incumbents in each period. Panel B shows the differences in steam adoption shares where the waterpower purchase price is higher (i.e., in counties with lower waterpower potential). Entrants and incumbents are more likely to use steam power in places with higher waterpower costs, in both periods, and this gap is larger among entrants. As a consequence, in places with many incumbents, there will be limited steam adoption in comparison to places where a greater share of firms are entrants.

This stylized model highlights how switching costs delay technology diffusion, despite substantial entry and exit, when some entrants continue to be drawn to the old technology. As a useful contrast, the quantitative model in Section IV will explore the faster transition dynamics when there are the same switching costs but the new technology is relatively suited to smaller less-productive firms.

Section IV also adds several useful features to the economic environment: (1) firm competition within a county, which allows for entrants to compete with and displace incumbents; (2) agglomeration effects in steam-use, which raise the prospect that firms' private steam adoption decisions may be inefficient from an aggregate perspective; and (3) shocks to firm productivity (φ_{jt}), which creates another mechanism for recurring lock-in even in steady state.

This initial stylized model provides guidance, however, on empirical patterns in the establishment-level data worth highlighting: steam adoption shares for entrants and incumbents, along with the distribution of mill size by power source due to the close relationship between mill size and mill productivity. The stylized model also suggests a reduced-form analysis by county water cost, focusing on early cross-sectional differences and relative changes in: the steam adoption share, the number of mills, entry and exit rates, and differences in entrant and water incumbent steam-use.

II Context and Data Construction

II.A From Water to Steam in US Mills

Flour and lumber mills were early users of mechanical power, which was initially water power (Hunter, 1979). Due to the high perishability and transportation costs of milled flour and lumber at the time, most flour and lumber mills served their "local clientele" and were needed throughout the country (Brown, 1923; National Industrial Conference Board, 1925; Kuhlmann, 1929). In places with lower waterpower potential, these mills were more expensive to build due to greater need for constructing dams, millponds, and riverwalls (Monroe, 1825).

The arrival of steam power provided a new source of mechanical power, particularly useful for places with less water power (Hunter, 1985; Sharrer, 1982). Steam was also more useful for mills that wanted to scale their production but it was not a strictly dominant technology because it required high non-variable costs: "the first cost of steam engines, and their annual expense, do not increase or diminish in proportion to the size of each engine" (Monroe, 1825). Steam equipment also required installation and continued maintenance oversight from trained engineers (Fisher, 1845). As a result, water power continued to be viable for smaller mills in particular.

The non-variable costs of steam declined nationally as the technology improved. Local installation and operation of steam power also drew on a growing local knowledge base as steam-use increased (Fisher, 1845; Greenberg, 1982). Most manufacturing establishments purchased equipment from local manufacturers (McLane Report, 1833; Woodbury Report, 1838; Temin 1966), and a quarter of steam equipment manufacturers report doing repair services in the Census of Manufactures. This growing knowledge base stands in contrast to the common and longstanding familiarity with water power (Weeden, 1890; Mullin and Kotval, 2021).

Contemporaneous accounts emphasize the importance of sunk costs as a barrier for millers to switch from water to steam power (Main et al., 1890). Other potential sources of switching barriers were less important in this context. The broader milling production process remained largely unchanged because steam power, like water power, provided rotational energy. Thus, mills did not require substantial adjustments to change power sources, though in other contexts these types of adjustment costs are important drivers of lock-in (David and Bunn, 1988; Bresnahan and Greenstein, 1996; Juhász, Squicciarini and Voigtländer, 2024). The outputs and inputs also remained the same, reducing lock-in from an existing customer base (Christensen, 1997) or needing to change suppliers (Farrell and Klemperer, 2007). This also meant that local steam and water mills were in direct competition with each other.

II.B Establishment-level Data, Census of Manufactures

We collected and digitized all known establishment-level manuscripts from the Census of Manufactures in 1850, 1860, 1870, and 1880. These data include the type of power used by each establishment, along with its total annual revenue, industry, county, and business name. Appendix A.1 discusses data coverage in detail, and how we group counties into time-consistent geographic units.

We focus on the lumber and flour milling industries, as they were widely mechanized before steam arrived, to study the transition of mechanical power from water to steam. Among lumber and flour mills in 1850, 91% report using either water or steam power.[1] Further, most waterpowered establishments were either flour or lumber mills in 1850. Flour milling was the largest industrial sector during our period, by revenue, and lumber milling was the largest by number of establishments.

Our sample includes 80,000 lumber and flour mills from 1850 to 1880. The sample covers 1,199 county-industries with at least one active mill in 1850 and non-missing data in each decade: 689 unique counties, with lumber mills in 613 counties and flour mills in 586 counties.

We created an establishment-level panel by hand-linking establishments over time using their business name, industry, product types, county, and (when available) nearest post office. We also trained a machine-learning algorithm to predict links, described in Appendix A.2.1, which allows us to analyze robustness to different link confidence thresholds and show that predicted link probabilities for our hand-links do not vary with county waterpower potential.

Our main interest is the diffusion of steam power, and how its adoption was shaped by the choices of entrants and incumbents. Notably, entrants in one period can become incumbents in the next period. We refer to "water incumbents" or "steam incumbents" as surviving

[1] Around 1% of mills used both water and steam power, which we classify as steam mills because they had already paid the fixed costs of steam. We omit non-mechanized mills from our main sample, which contributed little revenue share. Census schedules in 1870 and 1880 also asked mills for their installed horsepower: steam powered mills typically used more horsepower than water powered mills, and most mills used between 10-60 horsepower with the mode around 25 horsepower.

mills that used water or steam in the previous decade, regardless of their technology in the current period. Table 1 shows the share of milling in each decade for each type of mill. In each Census year, most mills entered during the previous decade, and entrant establishments disproportionately used more steam power than incumbent establishments.

Figure 3 shows that entrants were four times more likely to use steam power than water incumbents. As in the stylized model, entrants' decisions to adopt steam are a useful contrast to incumbents' decisions, because entrant firms start with a clean slate and do not face switching barriers. Switching barriers were not infinite, however, as both entrants and incumbents were more likely to adopt steam power over time. This is consistent with the technological improvements in steam power. Over the course of our sample, steam adoption rates increased by 62 percent for entrants and 55 percent for water incumbents, from a base rate of 29 percentage points for entrants and 8 percentage points for water incumbents (Figure 3).

Figure 4 shows that steam powered mills were larger than water powered mills, on average. Interpreted through the lens of the Melitz (2003) model, this pattern suggests that steam power had higher fixed costs but lower marginal costs than water power. Steam mills also had lower survival rates, despite being larger, suggesting higher fixed costs of staying in operation (Table 2). Appendix B discusses the cost structure of steam and water in detail.

Figure 4 also shows that the size distributions for steam and water powered mills converged over time. This indicates a decline in the fixed cost of steam power, as less-productive firms started to find steam power more attractive, whereas a declining marginal cost of steam power would have increased the size premium of steam powered mills. There continued to be substantial overlap in the size distributions of steam and water powered mills in each decade, however, which suggests an idiosyncratic component to mills' technology adoption.

II.C Measuring County Waterpower Potential

Counties' waterpower potential comes from the interaction of water flow and elevation changes along river segments. For each river segment, its theoretical horsepower potential is given by multiplying: (1) the flow rate of water (in cubic feet per second); (2) the change in elevation or fall height (in feet); and a gravitational constant. For this calculation, we use river segment data from the National Hydrography Dataset Plus (NHDPlusV2). We exclude the widest river segments, which were understood to be impractical for waterpower-use at the time and were used instead for transportation, and we use measured flow rates in the lowest three months to reduce the influence of smaller seasonal rivers that were less useful for consistent year-round water power.[2] Appendix A.3 describes in detail the waterpower

[2]We validate the NHDPlusV2 data with historical Census reports in Appendix A.3, though our measurement of county waterpower potential does not directly use the historical reports because they have

data, along with additional county-level data sources.

We calculate waterpower potential at the county level, summing over each river segment in the county and dividing by square miles. We define $LowerWaterpowerPotential_c$ as a negative standardized measure of (log) county waterpower potential per square mile, so its coefficient β can be interpreted as the effect of having one standard deviation lower waterpower potential.

Figure 5 Panel A shows the waterpower potential of our sample counties, with lighter shades representing lower waterpower potential. Panel B shows residual waterpower potential, after controlling for three types of county-level characteristics. First, to focus on the interaction of water flow and elevation changes, we control for the main effects of total county water flow and county ruggedness.[3] Second, because access to markets also affected economic activity and some mills got access to their material inputs through waterways (Cronon, 2009), we also control for: whether the county has navigable waterways; distance to the nearest navigable waterway; and county market access in 1850 including the waterway and railroad network (Atack, 2013; Donaldson and Hornbeck, 2016; Hornbeck and Rotemberg, 2024). Third, because coal was an important source of fuel for steam power, we control for: whether there are workable coal deposits in the county, the share of the county covered by coal deposits (Campbell, 1908), and access to coal via the transportation network.

III Estimated Differences by County Waterpower Potential

We first estimate how mill activity in 1850 varied with county waterpower potential. We then estimate the subsequent growth in lower waterpower counties, from 1850 to 1880. The contrasting responses of entrants and incumbents indicate switching barriers in steam adoption. These specifications also estimate target moments for the quantitative model in Section IV.

III.A Differences in 1850 by County Waterpower Potential

To estimate cross-sectional effects of county waterpower potential on lumber and flour mill activity, we estimate the following regressions where each observation is a county-industry:

$$Y_{ic} = \beta LowerWaterpowerPotential_c + \gamma_i X_c + \lambda_i + \varepsilon_{ic}. \quad (1)$$

We focus on the estimated pooled β, across lumber and flour mills, conditional on industry fixed effects λ_i and a set of county controls X_c whose effects vary by industry i. Our

non-random incomplete coverage based on historical economic activity.

[3] As fall height along river segments is not defined in the absence of rivers, county ruggedness is defined as each county's average terrain ruggedness index (Riley, DeGloria and Elliot, 1999), which is closely associated with changes in elevation.

baseline X_c include the three types of county characteristics described above (water flow and variable elevation, navigable waterways and market access, and coal access), and we discuss alternative controls and specifications in Appendix C.2. The identifying assumption is that, conditional on the included controls, counties with lower waterpower potential would have had similar mill activity in 1850 as those with higher potential, apart from differences due to waterpower availability.

Table 3 reports that counties with one standard deviation lower waterpower potential had substantially fewer water powered mills in 1850 (Panel A) and substantially less revenue from water powered mills in 1850 (Panel B). The estimated coefficients of -1.06 and -1.13 imply 65% fewer water powered mills and 68% less water powered revenue. Columns 2 and 3 report estimates separately for lumber mills and flour mills.

In 1850, there had already been faster adoption of steam power in counties with lower waterpower potential (Panels C and D). The share of mills using steam power in 1850 was 8.9 percentage points higher in these counties (Panel C), and the share of revenue produced using steam power was 13 percentage points higher (Panel D).

Counties with lower waterpower potential still had lower overall mill activity in 1850 (Panels E and F), though somewhat muted by the increased use of steam power. Particularly in lumber milling, where there was a more substantial early shift to steam power, there are more muted effects on total revenue in 1850.

III.B Relative Changes by County Waterpower Potential

To estimate changes over time, we estimate the following panel regressions where each observation is a county-industry-decade:

$$Y_{ict} = \beta_t LowerWaterpowerPotential_c + \gamma_{it} X_c + \lambda_{ic} + \lambda_{it} + \varepsilon_{ict}. \quad (2)$$

The estimated β coefficients report the relative change in counties with one standard deviation lower waterpower potential. We extend equation (1) to include fixed effects for county-industry (λ_{ic}) and year-industry ($\gamma_i t$), and interact the county controls with year-industry dummies ($\gamma_{it} X_c$). The identifying assumption is that counties with lower waterpower potential would have *changed* similarly, on average, apart from differences due to water power and steam. This assumption is conditional on differential changes associated with the county controls. We report robust standard errors clustered by county.[4]

[4]We also estimate standard errors that adjust for spatial correlation across counties, assuming counties are independent beyond a distance cutoff (Conley, 1999; Bergé, 2018). These standard errors are similar to our baseline clustered standard errors for distance cutoffs within 500 miles, and are 10-40% smaller for cutoffs up to 1000 miles.

Growth. Table 4 reports that steam adoption grew faster in counties with lower waterpower potential. From 1850 to 1860, the share of mills using steam power grew 6.8 percentage points more in counties with lower waterpower potential (Column 1). Steam-use continued to grow by 3.2 percentage points more from 1860 to 1870. Through the 1870s, steam adoption began to catch up in higher waterpower counties by a statistically insignificant 1 percentage point.

Counties with lower waterpower potential also experienced substantial relative growth in the total number of mills and total revenue (Table 4, Columns 2 and 3). The number of mills increased by 22% and revenue increased by 21% from 1850 to 1860. Growth continued at lower rates through 1880, suggesting continued benefits from earlier steam adoption in lower waterpower counties.

Crowd Out. Table 5 shows this growth was driven by entrant firms. The entry rate was 33% higher in lower waterpower counties, from 1850 to 1860, while the firm survival rate was 24% lower. In each period, entrants crowded-out local incumbent firms, which exited at higher rates in counties with lower waterpower potential despite the overall growth in these counties.

Table 6 shows that entrants were 16–19 percentage points more likely to be using steam power in counties with lower waterpower potential, in each decade, relative to entrants in counties with higher waterpower potential (Column 1). Water incumbents were also marginally more likely to switch to steam power in counties with lower waterpower potential (Column 2), but steam adoption by entrant mills was substantially more responsive than switching by water incumbents (Column 3). Recurring lock-in was quantitatively important, as new water incumbents are also less likely to adopt steam than entrants (Column 4).

III.C Interpretation of Reduced-form Results

Steam power allowed firms to scale production at lower effective marginal costs, but required higher fixed costs. Those fixed costs declined over our sample period as steam technology improved, which encouraged the adoption of steam and increased production, but the ability to take advantage of this opportunity was restricted by historical lock-in.

By 1850, counties with lower waterpower potential were using steam power at a higher rate, though still had lower total mill output (Table 3). Over the subsequent decades, those counties adopted steam power and increased output relatively faster (Table 4). The increase in steam-use for counties with lower waterpower potential was driven by entrants as incumbents were crowded out (Table 5). Entrants used steam at higher rates than incumbents (Figure 3) and more so in counties with lower waterpower potential, where entrants adopted steam more readily than water incumbents (Table 6).

Switching barriers would cause water incumbents' minimal switching to steam, compared to entrants' substantially greater adoption of steam. Switching barriers would also cause the increased exit of incumbents in counties with lower waterpower potential, even though total milling was growing substantially more in these counties.

Entrants are not subject to switching barriers, but some new firms entered using waterpower and survived to become incumbents in the next period—then facing switching barriers to adopt steam. This generates recurring lock-in, even when the initial locked-in incumbents have mostly exited the market. Indeed, only 2% of mills in 1880 existed in 1850, so most of the later incumbents were entrants at some point in our sample period. Switching barriers continued to slow technology diffusion, even with substantial entry and exit, because the relative cost structure of the old technology continued to draw in some entrants that became the next generation of locked-in incumbents. This recurring lock-in from earlier water-use is more pronounced in counties with higher waterpower potential.

IV A Quantitative Model of Technology Diffusion with Entry and Lock-in

While section III indicates a *relative* influence of switching barriers on the steam adoption of water incumbents compared to entrants, a drag on technological diffusion from lock-in also generates *aggregate* economic losses when early adopters generate positive externalities for later adopters. In this section, we quantify a dynamic equilibrium model of technology adoption and firm churn to assess the delay in diffusion caused by switching barriers and their aggregate consequences, even in a setting with substantial entry and exit. We extend the stylized model from Section I to incorporate firm-level idiosyncratic shocks, endogenous entry and exit, competition within local markets, and local agglomeration effects in steam use. We parameterize and estimate the model drawing on the descriptive patterns and reduced-form results described in the previous sections.

Firms make dynamic power source choices in the model, in which neither power technology is dominant: water power has a lower fixed adoption cost, but steam has lower marginal costs of production that enable greater scale. Incumbents face barriers in switching to steam, due to their sunk investments in water power.

The purchase price of steam is falling over time, as the technology improves, whereas the cost of adopting water power varies across counties. We simulate the transition path where forward-looking firms anticipate technological improvements and their equilibrium implications. For example, while lower steam costs create an option value for water entrants to eventually switch to steam, cheaper steam may also induce increased competition for customers.

Anticipation of switching barriers encourages firms to enter using steam, though some less-productive firms still choose to enter using water power. If those water-powered entrants survive, they may have a greater desire to adopt steam if their productivity grows, but they have then become a new generation of incumbents facing switching barriers from their sunk investments.

IV.A Static Choices: Production and Demand

We extend the production function in Section I to include the potential for agglomeration forces in power use. Firm j in county c and year t uses a constant returns to scale production technology in flexible inputs x:

$$y_{jct} = \exp(\varphi_{jct} + \gamma_{R_{jct}} + \alpha_{R_{jct}} s_{ct}) x_{jct}. \tag{3}$$

Firm productivity depends on a baseline φ_{jct} and an additional $\gamma_{R_{jct}}$ from their rotational power choice R: water (W) or steam (S). Steam productivity depends on the share of firms using steam in the county (s_{ct}), where α_S captures the strength of this local agglomeration force.[5] We normalize the agglomeration force in water power to zero, so α_S captures the net agglomeration force in steam power.

Demand for mill products is local, within a county, with a total demand elasticity η and an elasticity of substitution between mills ϵ. Firm profits are a function of power choice and baseline productivity:

$$\pi_{ct}(R, \varphi) = \frac{1}{\epsilon} P_{ct}{}^{\epsilon-\eta} \left(\frac{\epsilon}{\epsilon - 1} \frac{w}{\exp(\varphi + \gamma_R + \alpha_R s_{ct})} \right)^{1-\epsilon}, \tag{4}$$

where the price index reflects competition between mills ($P_{ct} = \left[\int p_{jct}^{1-\epsilon}\, dj\right]^{\frac{1}{1-\epsilon}}$) and inputs x are supplied elastically at cost w.

Steam affects firm profits through two countervailing forces: while adopting the technology boosts productivity (if $\gamma_S, \alpha_S > 0$), its availability to other mills also strengthens competition (lowering P_{ct}).

IV.B Dynamic Choices: Firm Entry and Power Choice

We model the firm's dynamic problem in four stages: (1) entry, (2) productivity draws, (3) exit, (4) power choice and production.

[5] We focus on local agglomeration forces, which reflect the local knowledge base surrounding the adoption and operation of steam power (see Section II). Knowledge spillovers are often geographically localized (Feldman and Kogler, 2010), though, to the extent some effects propagate to broader geographic areas (Giroud et al., 2024), the inefficiently low steam adoption we capture in the model would understate the aggregate inefficiency.

Stage 1: Entry. A prospective firm enters county c if its expected continuation value after entry exceeds the fixed cost of entry: $\mathbb{E}_\varphi \left[V_{ct}(E, \varphi)\right] \geq f^e$.[6]

Stage 2: Productivity Draws. Incumbent firms update their productivity following an AR(1) process: $\varphi_{jct} = \pi \varphi_{jct-1} + \sigma \xi_{jct}$, where $\xi_{jct} \overset{\text{iid}}{\sim} \mathcal{N}(0, 1)$. Entrants draw their productivity from the stationary distribution of the same AR(1) process, which implies $\varphi_{jct} \overset{\text{iid}}{\sim} \mathcal{N}\left(0, \frac{\sigma^2}{1-\pi^2}\right)$.

Stage 3: Exit. Each firm chooses to operate or exit, given its revealed productivity and fixed operating costs. Each power source has a different fixed component of its operating cost (f_o^R), and firms additionally draw idiosyncratic operation and exit costs from a Gumbel distribution: $\nu_{jct}^R(0/1) \overset{\text{iid}}{\sim} \mathit{GEV1}(\rho_o)$. Firms compare the expected value of sinking those costs with the value of exit: $V_{ct}(R, \varphi) = \max\{\mathbb{E}_\varepsilon \left[V_{ct}^o(R, \varphi)\right] - f_o^R - \nu_{jct}^R(0), \omega^R c_{ct}(R) - \nu_{jct}^R(1)\}$, where $\mathbb{E}_\varepsilon \left[V_{ct}^o(R, \varphi)\right]$ is the expected value of operating, and ω^R is the share of investment in power infrastructure that is recovered upon resale.

Stage 4: Power Choice and Production. Operating firms are either: (1) entrants E, who are choosing a power source for the first time; or (2) incumbents who have already invested in water or steam power. For entrants, there is a purchase price for each power source ($c_{ct}(R')$). For incumbents, the cost of switching from power R to power R' is the purchase price, net of liquidation value of prior investment, and any other residual switching barriers: $c_{ct}(R, R') = c_{ct}(R') - \omega^R c_{ct}(R) + c(R, R')$. The purchase price of steam is a function of the national cost and local agglomeration (or congestion): $c_{ct}(S) = c_t(S) + \kappa s_{ct}$.

For both entrants and water incumbents, the decision to use steam power trades off greater flow profits from operating a more-productive technology with the greater fixed costs from adopting the new technology:

$$V_{ct}^o(R, \varphi) = \max_{R' \in \{W, S\}} \{\pi_{ct}(R', \varphi) - c_{ct}(R, R') - \varepsilon_{jct}(R') + \delta \mathbb{E}_{\varphi'} \left[V_{ct+1}(R', \varphi')\right]\}, \tag{6}$$

where δ is a discount factor and firms draw idiosyncratic power usage costs $\varepsilon_{jct}(R)$ from a Gumbel distribution: $\varepsilon_{jct}(R) \overset{\text{iid}}{\sim} \mathit{GEV1}(\rho)$.[7]

After these four stages, entrants are now incumbents in the next period and the four-stage cycle repeats.

[6] We follow Hopenhayn (1992), where firms are ex ante homogeneous, draw productivity upon entry, and then decide whether to operate based on this draw. An alternative and complementary approach, developed by Buera and Trachter (2024), assumes that firms draw productivity before incurring entry costs, thereby allowing selection on the entry margin as well.

[7] The use of Gumbel distributions follows Rust (1987) and implies that policy functions take a logit form. For example, the probability of choosing power source $R' \in \{W, S\}$ for a mill with existing power source R is: $\Pr_{ct}(R'|R, \varphi) = \frac{\exp\left(\frac{1}{\rho}(-c_{ct}(R,R') + \pi_{ct}(R',\varphi) + \delta \mathbb{E}_{\varphi'}[V_{ct+1}(R',\varphi')])\right)}{\sum_{R'' \in \{W,S\}} \exp\left(\frac{1}{\rho}(-c_{ct}(R,R'') + \pi_{ct}(R'',\varphi) + \delta \mathbb{E}_{\varphi'}[V_{ct+1}(R'',\varphi')])\right)}$.

IV.C Equilibrium

We model the equilibrium in counties that differ in their costs of water power ($\frac{\partial c_{ct}(W)}{\partial WPP} < 0$), studying their transition paths from 1830 to 1900 as steam costs decline ($\frac{\partial c_{ct}(S)}{\partial t} < 0$). In equilibrium, heterogeneous firms make forward-looking decisions about entry, exit, and power adoption, and firms' decisions are interlinked through their competition in county product markets and agglomeration spillovers in steam power choices. Formally, an equilibrium for county c is a time path for the mass of entrants M_{ct}, the mass of operating firms $F_{ct}(R, \varphi)$, and the policy functions for operation/exit $O_{ct}(R, \varphi)$ and power $R'_{ct}(R, \varphi)$, taking the time path of steam costs $c_{ct}(S)$ as given, such that:

1. Firms enter, exit, and adopt power sources to maximize expected discounted profits.

2. Firms source inputs x to maximize flow profits period-by-period.

3. Output markets clear: $P_{ct}Y_{ct} = wX_{ct} + \Pi_{ct}$, where $Y_{ct} = \int y_{ct}(R, \varphi) dF_{ct}(R, \varphi)$ is total local sales, $\Pi_{ct} = \int \pi_{ct}(R, \varphi) dF_{ct}(R, \varphi)$ is total local profits and, $X_{ct} = \int x_{ct}(R, \varphi) dF_{ct}(R, \varphi)$ is local demand for inputs.

4. The free entry condition holds: $\mathbb{E}_{\varphi} \left[V_{ct}(E, \varphi) \right] \leq f^e$.

5. The evolution of firm masses $\{F_{ct}\}_t$ is consistent with the policy functions $\{O_{ct}, R'_{ct}\}_t$.

Appendix D describes how we solve and simulate the model economy, including the existence and uniqueness of equilibrium. In brief, we solve firms' dynamic programs using value function iteration in steady state and backward recursion along the transition path. We compute the path of entrants using a Newton–Raphson shooting algorithm applied to the system of free-entry conditions, and solve the dynamic equilibrium in the aggregate state variables using a fixed-point algorithm.

IV.D Structural Estimation

We use the Method of Simulated Moments (MSM) to estimate 15 parameters. Table 7 reports the 15 parameters that include power switching costs, other costs (startup, power adoption, operation), productivity parameters, and agglomeration effects.

We estimate the parameters jointly using 15 targeted moments, though individual parameters have an intuitive mapping to particular moments that we discuss in more detail in Appendix D.3. We also formalize the local relationships between structural parameters and simulated moments following Andrews, Gentzkow and Shapiro (2017). Establishment-level moments help identify micro-level parameters, such as power switching barriers, and county-level moments help identify market-level parameters like agglomeration effects.

We continue to draw on variation in county waterpower potential for identification, which provides a shifter in the local cost of water power, using the same specification from Section III to control for other factors that might influence local manufacturing activity. The estimation procedure matches the 15 target moments almost exactly, while also largely reproducing other non-targeted estimates from Tables 4–6 for how lower waterpower potential affected steam adoption and growth among entrants and incumbents in simulated data from our model (see Appendix D.3).

Table 7 reports the estimated parameters.[8] Appendix D.3 discusses the estimated parameters in detail, comparing the estimated magnitudes to contemporaneous sources and other literature.

Here, we highlight three features of the estimated model governing the diffusion of steam power, recurring lock-in of water entrants, and aggregate inefficiencies arising from agglomeration spillovers in steam adoption.

Power Costs. We estimate that steam power offers 9% lower marginal costs of production at the expense of three times higher fixed costs of operating. These estimates reflect that steam users have larger optimal scales of production (as in Figure 4) but lower rates of survival (as in Table A.5).[9] Figure 6 shows how the purchase price of steam power falls over time, which is the driving force in the transition to steam. Steam initially had a 2.4 times higher purchase price than water, but as the technology improved, its purchase price eventually fell below that of water. However, the continued higher operating costs of steam (along with its initially higher purchase price), meant that water power continued to be appealing to less-productive entrants and caused recurring lock-in.

Switching Barriers. The estimated switching cost from water to steam power is closely related to the difference in steam adoption shares for entrants versus water incumbents, as in Figure 3.[10] Sunk investments in water power account for 93% of the overall switching cost, which we estimate is roughly two months of revenue, with the residual switching cost only representing 1.4% of annual sales. This implies that other forces that could make it difficult for enterprises to adopt new technologies, such as retrofitting costs, financial frictions, or behavioral factors, are likely quantitatively less important in this setting.

[8] Table 7 also reports 5 parameters that we calibrate outside the estimation routine: the firm demand elasticity ($\epsilon = 6$), the discount factor ($\delta = 0.94$), sunk cost share ($1 - \omega^R$=1), the convergence rate for steam technology ($c_S^{(slope)} = 4\%$), and the dispersion of cost shocks ($\rho = \rho_o = 2$). Appendix D.3 provides details for this calibration, which uses variation in mill sales and costs along with estimates from the literature.

[9] It may initially seem surprising that steam power production could have lower marginal costs, but its higher operational costs were broadly fixed operating costs that did not scale with production.

[10] The estimated switching cost uses the within-county difference in this adoption rate. By jointly estimating parameters, the model estimation also adjusts for differences between entrants and water incumbents in their productivity and scale.

Agglomeration Spillovers. Of particular interest is the agglomeration effect in steam productivity (α_S), which boosts output as steam use increases. This agglomeration effect in steam power has an important role in determining whether there are aggregate inefficiencies from lock-in. The most relevant moment is the growth of revenue from 1850 to 1880 in counties with lower waterpower potential, as in Table 4. In particular, total revenue grew faster than can be explained by firms' internalized benefits from steam adoption. If we assume $\alpha_S = 0$ and re-estimate the model, the other parameters are similar, but the model predicts only half the observed relative growth in revenue from 1850 to 1880 in lower waterpower counties (Table A.19, Column 4).

We also allow for agglomeration or congestion effects in steam purchase prices (κ), but do not estimate this to be an important driver of steam adoption as the estimated κ is small relative to the purchase price of steam. Further, if we assume $\kappa = 0$ and re-estimate the model, the constrained model nevertheless still matches the differential steam adoption and economic growth in lower waterpower counties (Table A.19, Column 5). This suggests that limited local awareness of steam power was not a primary barrier to adoption: having more steam-using neighbors did not make mills more likely to adopt steam, other than through the estimated local productivity spillover.[11]

Appendix D.3 reports standard errors for our structural parameters, computed using the Delta method. The model's key features are precise, with statistically significant differences across time and space: higher but declining fixed costs of steam, lower water costs in low–water-power regions, and positive agglomeration effects in steam production.

V Counterfactuals

We begin by examining how limited access to waterpower creates an advantage of backwardness in regions' response to steam (Gerschenkron, 1962). We show how recurring lock-in slows the adoption of steam power. Firms have private incentives to become locked into the old technology and remain there, which we show generates aggregate inefficiency along the transition path and in steady state. Finally, we show that if the new technology primarily benefited smaller rather than larger establishments, recurring lock-in would not slow technological adoption.

V.A Waterpower Potential and the Advantage of Backwardness

Figure 7, Panels A and B, simulate the transition to steam power in our baseline region and in a region with one standard deviation lower waterpower potential. Panel A plots the

[11]While we formally model κ as affecting the price of steam power, it functionally serves as a local shifter for the *relative* price of steam. If the price of local water power decreases in the local use of steam, due to a move along the supply curve for water power (in the spirit of Hansen and Prescott 2002), we would estimate a positive κ.

share of steam adoption, and Panel B shows the resulting changes in milling activity. These simulations extend the reduced-form analysis in Section III, which identifies only *differences* between regions, by tracing how steam power affects the *levels* of power use and milling activity in each region along their transition to steady state.

Limited water access creates an "advantage of backwardness" in steam adoption: the region with lower waterpower potential reaches the baseline region's steady-state steam share 38 years sooner and ultimately attains a 17 percentage point higher steady-state steam share. This advantage arises not only because steam is more useful in such places, but also because firms there face fewer switching barriers from earlier water use. Initially, the lower waterpower region is constrained by its limited water access, with mill revenues in 1830 roughly 78% below those in the baseline. Over time, however, the agglomeration force generated by greater steam adoption becomes strong enough to offset the disadvantage to water power users. As a result, aggregate mill revenues in the lower water power region fully catch up with those in the baseline region—despite the continued relevance of water power, even in steady state.

V.B Recurring Lock-in from Switching Barriers

Panels C and D of Figure 7 examine how establishment-level switching barriers affect aggregate steam adoption and mill revenues. We simulate the arrival of steam power under two counterfactual scenarios: a "No Water Lock-In" scenario, in which water mills face no switching barriers ($\omega^W = 1$, $c(W, S) = 0$); and a Full Water Lock-in" scenario, in which switching barriers are prohibitively high ($c(W, S) \to \infty$). Entrants are free to choose their power source in all scenarios.

Panel C shows that establishment-level switching barriers substantially delay aggregate steam adoption, despite ongoing entry and exit. The economy reaches a 30% steam adoption rate 23 years faster when water mills face no switching barriers, compared to the scenario with full water lock-in (1854 vs. 1877). The slower steam adoption in the lock-in scenario reflects *recurring lock-in*: mills adopt water power at entry despite fully anticipating that they may later become locked into an inferior technology.

Recurring lock-in is most pronounced during the middle of the transition, when steam technology is improving and more establishments are on the margin of choosing steam power. Yet, switching barriers also matter in steady state: because mill productivity evolves stochastically, some mills grow more productive over time, causing switching barriers to bind even in the steady state. As a result, steady-state steam adoption is six percentage points lower under full lock-in.

Steam adoption rates in our observed baseline economy fall roughly halfway between the

"Full Water Lock-In" and "No Water Lock-In" scenarios. Our observed baseline economy is closer to the "Full Water Lock-In" scenario early on the adoption curve and, over time, converges to the "No Water Lock-In" scenario. Technology switching is particularly important for the acceleration in steam adoption that we see in our data period, from 1850 to 1880.

Panel D shows the impact of switching barriers on total mill revenue. Switching barriers among water mills continue to hamper the economic potential of steam power, and are largest in the steady state when steam technology is fully mature. Without water lock-in, the steady state gains in total revenue from steam power would be 2.9 times larger. These gains arise because there would be more entry without switching barriers, as firms value the option of costlessly switching to steam in the future. This substantially increases the number of active mills in the no lock-in scenario, whereas total revenue in the baseline economy is closer to the scenario with full water lock-in.

While eliminating lock-in directly benefits water incumbent mills, costless switching also creates competition by encouraging new entry and switching among other water incumbents. Quantitatively, removing switching barriers raises competition enough that, on net, the initial incumbents do not benefit from the arrival of steam power. See Appendix D.4.1 for discussion of the incidence of steam power on incumbent and entrants, along with consumers who are the main beneficiaries through increased output and lower prices.

V.C Quantifying Recurring Lock-in Along the Transition and in Steady-State

To connect our quantitative estimates with the stylized model in Section I, we can calculate the share of potential steam users that are locked into water power. Specifically, we calculate for each establishment whether it *would* adopt steam if it were currently an entrant ("unrestricted steam user"), and compare this total to the actual number of steam users. The share of firms locked-in is given by the difference in unrestricted and actual steam users, divided by the number of unrestricted steam users.[12] This captures how much aggregate steam use is constrained by lock-in, in each period. The extent of lock-in is one-third in 1850 and one-sixth in steady state, falling along the transition path though remaining important even as the cost of steam power stabilized.

V.D Aggregate Inefficiencies Along the Transition and in Steady-State

Given the estimated agglomeration effects in steam-use, there will be a difference between firms' private incentives to adopt steam and the socially optimal incentives to adopt steam. Firms consider only their private benefits and costs, in the model, and do not value how their adoption of steam power benefits other steam users. We now turn to illustrating the

[12]This corresponds to, in Figure 1, firms in the light gray areas of regions II and III, relative to all firms in regions II-V.

aggregate inefficiency from lock-in, due to agglomeration effects in steam-use, both along the transition path and in steady state.

We evaluate a thought experiment: mitigating sunk costs by allowing waterpowered establishments to sell their water power infrastructure.[13] This has effects along three margins: (1) gains in producer surplus, from lower costs of switching to steam; (2) gains in consumer surplus, from decreased output prices; and (3) losses from expenditure on the old water infrastructure, which is removed from the economy.[14] We report these effects as a share of current output, so the magnitudes can be interpreted like aggregate productivity changes. To maintain consistent magnitudes across scenarios, we set the rate of partial irreversibility such that the expenditure on the old water infrastructure is always equal to 1% of baseline output.

Table 8, Column 1, reports the effects of eliminating sunk costs during the transition to steam power in 1850 (Panel A) and in steady state (Panel B). In 1850, the counterfactual water purchases would raise producer surplus by 0.5 percent of output and consumer surplus by 11.4 percent, implying a net gain worth roughly 11 percent of output.

In steady state, the effects are even larger: increasing producer surplus by 0.7 percent and consumer surplus by 22.3 percent, yielding a net gain worth roughly 22 percent of output. Because producer surplus rises by less than the cost of the water infrastructure, producers would not collectively benefit from a coordinated big push toward steam.

These effects are large, especially for consumers, because of induced entry. Encouraging steam switching raises the productivity of steam power for all users, which in turn induces more firms to enter and adopt steam power, even though entrants do not receive any reduction in their purchase costs. Column 2 shows that this endogenous entry response is an important driver of the aggregate gains from removing switching costs. In particular, if we fix the mass of entrants along the entire path (M_{ct}) as in the baseline environment with untouched switching costs, the consumer gains fall to 1–2 percent of output. When free entry is shut down, some surplus is left for entrants to capture. However, those gains are small, and the overall benefits from removing switching costs are substantially reduced—though still positive on net.

Across both scenarios, the gains are larger in steady-state than along the transition. This finding may appear surprising, as Section V.C shows the extent of lock-in is larger along the transition than in steady state. There are more steam users in steady state, though, who benefit from increasing the number of steam users and increase output and lower prices for

[13]The counterfactual we consider is a temporary shock, lasting for one period.

[14]Note that incumbent firms and consumers are the only two groups whose surplus is affected in the baseline economy, as the free entry condition implies that entrants' rents are zero in equilibrium.

consumers. Thus, the inefficiency from lock-in is larger when there are more firms that would benefit from the agglomeration effects.

Table 8 Column 3 shows that the agglomeration effect is required for there to be aggregate inefficiency from lock-in. For this exercise, we re-simulate the model without agglomeration effects (forcing $\alpha = \kappa = 0$). In this alternative environment, mitigating sunk costs does lead some incumbents to adopt steam, but the gains in producer and consumer surplus are smaller than the capital expenditure. Intuitively, without agglomeration externalities, distorting firms' technology choices leads to an aggregate loss.

This exercise also illustrates that the estimated agglomeration effects are not strong enough to create an additional equilibrium with higher steam use. Mitigating sunk costs immediately doubles the share of mills using steam power in the baseline scenario, but the steam share converges back to baseline within 15 years (Figure 8). Despite this convergence, though, there are still substantial aggregate gains, due to the agglomeration effects.

Overall, lock-in generates aggregate inefficiencies both during the transition to steam power and in steady-state. These effects are heightened by endogenous entry, as greater steam-use encourages further steam-use through agglomeration effects, even though the economy converges to the same equilibrium as firms turn over and lock-in re-emerges.

V.E Fixed Costs and The Speed of Technology Diffusion

We began with the idea that the widespread adoption of new technology can be remarkably fast or slow. We showed that steam adoption was substantially slowed by recurring lock-in, but many other new technologies diffuse quickly. We now illustrate when recurring lock-in does *not* delay technology diffusion, even in settings with substantial switching costs.

In particular, the delay in technology adoption requires both switching costs *and* the old technology to have a relatively lower purchase price. When the old technology has a lower purchase price and higher marginal cost, it continues to draw in some entrants who sometimes survive to become future locked-in incumbents, slowing the pace of technology adoption.

To show this, we consider two hypothetical technologies that are equally attractive (so their steady-state adoption rates are 50%) but differ in their purchase prices and marginal costs. Technology 1 ("High FC & low MC") has a marginal cost advantage that matches our estimated advantage of steam over water. Technology 2 ("Low FC & high MC") has a lower fixed adoption cost, calibrated to yield the same 50% steady-state adoption rate. All other parameter values (e.g., demand elasticities, overhead costs, and idiosyncratic shocks) are fixed at those we estimate for water power.

Figure 9 plots the adoption dynamics of each technology, conditional on which one is initially in place. As a benchmark, the gray line shows the importance of switching costs: if the economy starts with technology 2 and an *identical* technology is introduced, it takes three years to approach steady-state adoption (defined here as reaching a 47% adoption share).[15]

The black line shows that higher fixed costs slow diffusion: if technology 1 is introduced into an economy initially using technology 2, it takes 16 years to reach 47% adoption. By contrast, the dashed line shows that lower fixed costs accelerate adoption: if technology 2 is introduced into an economy initially using technology 1, it reaches 47% adoption in its first year.[16]

These dynamics are all driven by the interaction of fixed costs and switching barriers: in the absence of switching barriers, adoption would immediately reach its steady state level, regardless of the relative cost structures.

VI Conclusion

This paper studies the prolonged diffusion of steam power in the 19th century United States. We compile a full panel dataset of lumber and flour mills, showing that: mills in counties with less waterpower potential adopted more steam power, earlier, but steam adoption was driven predominantly by entrant mills. Incumbents rarely changed power technologies due to switching barriers from sunk investments in water power.

We emphasize dynamic effects, through which prior use of water power (1) created lock-in effects discouraging steam adoption (both for the initial incumbents and subsequent generations of entrants), (2) generated leapfrogging by entrants, and (3) made steam adoption inefficiently slow due to agglomeration spillovers.

When there are agglomeration spillovers, recurring lock-in generates aggregate inefficiency both along the technology transition path and in steady state. For general purpose technologies, like steam power, it is natural to think about early adopters having substantial benefits through encouraging others to adopt the technology. While individual firms may make privately optimal technology adoption decisions, inefficiencies arise from firms not internalizing that their use of the new technology raises others' productivity.

Encouraging firms to adopt new technologies can generate aggregate gains even under "weak" agglomeration spillovers, which are insufficient to generate "big push" dynamics — or a permanent shift in steam adoption from temporary subsidies. Without any agglomeration

[15] The steady-state share of firms using the new technology asymptotically trends to 50%, so we report the duration to reach an adoption rate of 47%.

[16] When the new technology has relatively low fixed costs, it overshoots upon introduction and reaches over 50% adoption. This is because, initially, the price index is relatively high and so low-productivity establishments (who prefer technology 2) are initially able to profitably produce before getting crowded out in steady state.

effects, however, there are net losses from distorting firms' technology adoption decisions.

We estimate a dynamic equilibrium model of entry and investment to characterize the forces that determine technology diffusion. We find that the interaction of high fixed costs and switching barriers delays aggregate technology adoption. For technologies with both of these features, the entry of new firms is not a panacea against technological lock-in. High fixed costs made smaller entrants predisposed to use the old technology (the low-initial-cost and high-marginal-cost technology). Switching barriers then meant that these entrant firms became stuck with the old technology, even though the barriers were anticipated. Either feature on its own has little effect on adoption speeds.

Many recent quickly-embraced innovations, such as cloud computing and large language models (Lu, Phillips and Yang, 2023; Humlum and Vestergaard, 2025), allow small firms to use new technologies without substantial fixed investments. Energy transitions have historically been protracted (Smil, 2014), and many modern environmentally friendly technologies, such as heat pumps and renewable energy sources, are associated with low marginal costs but high fixed costs and switching barriers. Our results highlight how these characteristics can lead to inefficiently slow adoption, as new enterprises use old technologies and become locked-in.

References

Abramitzky, Ran, Leah Boustan, Katherine Eriksson, James Feigenbaum, and Santiago Pérez. 2021. "Automated Linking of Historical Data." *Journal of Economic Literature*, 59(3): 865–918.

Acemoglu, Daron, and Fabrizio Zilibotti. 2001. "Productivity Differences." *The Quarterly Journal of Economics*, 116(2): 563–606.

Acemoglu, Daron, Ufuk Akcigit, Harun Alp, Nicholas Bloom, and William Kerr. 2018. "Innovation, Reallocation, and Growth." *American Economic Review*, 108(11): 3450–91.

Aghion, Philippe, Antonin Bergeaud, Maarten De Ridder, and John Van Reenen. 2024. "Lost in Transition: Financial Barriers to Green Growth." *Working Paper.*

Aghion, Philippe, Lint Barrage, Eric Donald, David Hémous, and Ernest Liu. 2025. "Transition to Green Technology Along the Supply Chain." *Working Paper.*

Allen, Robert C. 2009. *The British Industrial Revolution in Global Perspective.* Cambridge, England: Cambridge University Press.

Alvarez, Fernando, David Argente, Francesco Lippi, Esteban Méndez, and Diana Van Patten. 2023. "Strategic Complementarities in a Dynamic Model of Technology Adoption: P2P Digital Payments." *Working Paper.*

Andrews, Isaiah, Matthew Gentzkow, and Jesse M. Shapiro. 2017. "Measuring the Sensitivity of Parameter Estimates to Estimation Moments." *The Quarterly Journal of Economics*, 132(4): 1553–1592.

Arcidiacono, Peter, and Robert A. Miller. 2011. "Conditional Choice Probability Estimation of Dynamic Discrete Choice Models with Unobserved Heterogeneity." *Econometrica*, 79(6): 1823–1867.

Armistead, W.K., Thomas Lawson, and S.H. Long. 1841. "Report of the Board of Officers Appointed to Select a Suitable Site of the Establishment of a National Armory on the Western Waters." *House Documents, Otherwise Published as Executive Documents: 13th Congress, 2d Session-49th Congress, 1st Session, Volume 4.* Washington, D.C.

Armitage, Sarah. 2023. "Technology Adoption and the Timing of Environmental Policy: Evidence from Efficient Lighting." Social Science Research Network Working Paper 4108312.

Arrow, Kenneth J. 1962. "The Economic Implications of Learning by Doing." *The Review of Economic Studies*, 29(3): 155–173.

Ashraf, Quamrul H., Francesco Cinnirella, Oded Galor, Boris Gershman, and Erik Hornung. 2024. "Structural Change, Elite Capitalism, and the Emergence of Labor Emancipation." *The Review of Economic Studies.*

Asker, John, Allan Collard-Wexler, and Jan de Loecker. 2014. "Dynamic Inputs and Resource (Mis)Allocation." *Journal of Political Economy*, 122(5): 1013–1063.

Atack, Jeremy. 1979. "Fact in Fiction? The Relative Costs of Steam and Water Power: A Simulation Approach." *Explorations in Economic History*, 16(4): 409–437.

Atack, Jeremy. 2013. "On the Use of Geographic Information Systems in Economic History: The American Transportation Revolution Revisited." *Journal of Economic History*, 73: 313—-338.

Atack, Jeremy, and Fred Bateman. 1999. "Nineteenth-Century US Industrial Development through the Eyes of the Census of Manufactures: A New Resource for Historical Research." *Historical Methods: A Journal of Quantitative and Interdisciplinary History*, 32(4): 177–188.

Atack, Jeremy, and Robert A. Margo. 2019. "Gallman Revisited: Blacksmithing and American Manufacturing, 1850–1870." *Cliometrica*, 13(1): 1–23.

Atack, Jeremy, Fred Bateman, and Robert A. Margo. 2008. "Steam Power, Establishment Size, and Labor Productivity Growth in Nineteenth Century American Manufacturing." *Explo-*

rations in Economic History, 45(2): 185–198.

Atack, Jeremy, Fred Bateman, and Thomas Weiss. 1980. "The Regional Diffusion and Adoption of the Steam Engine in American Manufacturing." *The Journal of Economic History*, 40(2): 281–308.

Atack, Jeremy, Robert A. Margo, and Paul W. Rhode. 2019. "'Automation' of Manufacturing in the Late Nineteenth Century: The Hand and Machine Labor Study." *Journal of Economic Perspectives*, 33(2): 51–70.

Atack, Jeremy, Robert A. Margo, and Paul W. Rhode. 2022. "'Mechanization Takes Command?': Powered Machinery and Production Times in Late Nineteenth-Century American Manufacturing." *The Journal of Economic History*, 82(3): 663–689.

Atkeson, Andrew, and Patrick J. Kehoe. 1999. "Models of Energy Use: Putty-Putty versus Putty-Clay." *American Economic Review*, 89(4): 1028–1043.

Atkeson, Andrew, and Patrick J. Kehoe. 2007. "Modeling the Transition to a New Economy: Lessons from Two Technological Revolutions." *American Economic Review*, 97(1): 64–88.

Bachmann, Rüdiger, and Christian Bayer. 2014. "Investment Dispersion and the Business Cycle." *American Economic Review*, 104(4): 1392–1416.

Bahk, Byong-Hyong, and Michael Gort. 1993. "Decomposing Learning by Doing in New Plants." *Journal of Political Economy*, 101(4): 561–583.

Bailey, Martha J., Connor Cole, Morgan Henderson, and Catherine Massey. 2020. "How Well do Automated Linking methods perform? Lessons from US Historical Data." *Journal of Economic Literature*, 58(4): 997–1044.

Basu, Susanto, and David N. Weil. 1998. "Appropriate Technology and Growth." *The Quarterly Journal of Economics*, 113(4): 1025–1054.

Bazzi, Samuel, Martin Fiszbein, and Mesay Gebresilasse. 2020. "Frontier Culture: The Roots and Persistence of 'Rugged Individualism' in the United States." *Econometrica*, 88(6): 2329–2368.

Benhabib, Jess, and Aldo Rustichini. 1991. "Vintage Capital, Investment, and Growth." *Journal of Economic Theory*, 55(2): 323–339.

Benhabib, Jess, Jesse Perla, and Christopher Tonetti. 2021. "Reconciling Models of Diffusion and Innovation: A Theory of the Productivity Distribution and Technology Frontier." *Econometrica*, 89(5): 2261–2301.

Bergé, Laurent. 2018. "Efficient Estimation of Maximum Likelihood Models with Multiple Fixed-Effects: The R Package FENmlm." Department of Economics at the University of Luxembourg DEM Discussion Paper Series 18-13.

Bishop, Paul, and Esperanza Muñoz-Salinas. 2013. "Tectonics, Geomorphology and Water Mill Location in Scotland, and the Potential Impacts of Mill Dam Failure." *Applied Geography*, 42: 195–205.

Bleakley, Hoyt, and Jeffrey Lin. 2012. "Portage and Path Dependence." *The Quarterly Journal of Economics*, 127(2): 587–644.

Bloom, Nicholas. 2009. "The Impact of Uncertainty Shocks." *Econometrica*, 77(3): 623–685.

Bloom, Nicholas, Benn Eifert, Aprajit Mahajan, David McKenzie, and John Roberts. 2013. "Does Management Matter? Evidence from India." *The Quarterly Journal of Economics*, 128(1): 1–51.

Bresnahan, Timothy, and Shane Greenstein. 1996. "Technical Progress and Co-invention in Computing and in the Uses of Computers." *Brookings Papers on Economic Activity. Microeconomics*, 1996: 1–83.

Bresnahan, Timothy F., and M. Trajtenberg. 1995. "General Purpose Technologies 'Engines of Growth'?" *Journal of Econometrics*, 65(1): 83–108.

Broda, Christian, and David E. Weinstein. 2006. "Globalization and the Gains from Variety." *The Quarterly Journal of Economics*, 121(2): 541–585.

Brown, Nelson Courtlandt. 1923. *The American Lumber Industry: Embracing the Principal Features of the Resources, Production, Distribution, and Utilization of Lumber in the United States.* New York: J. Wiley & Sons.

Buera, Francisco, Hugo Hopenhayn, Yongseok Shin, and Nicholas Trachter. 2021. "Big Push in Distorted Economies." *Working Paper.*

Buera, Francisco J., and Nicholas Trachter. 2024. "Sectoral Development Multipliers." *Working Paper.*

Burke, John G. 1966. "Bursting Boilers and the Federal Power." *Technology and Culture*, 7(1): 1–23.

Bustos, Paula. 2011. "Trade Liberalization, Exports, and Technology Upgrading: Evidence on the Impact of MERCOSUR on Argentinian Firms." *American Economic Review*, 101(1): 304–40.

Cabral, Luís M.B., and Jose Mata. 2003. "On the Evolution of the Firm Size Distribution: Facts and Theory." *American Economic Review*, 93(4): 1075–1090.

Campbell, Marius R. 1908. "Coal Fields of the United States." *United States Geological Survey, Washington, D.C.*

Caunedo, Julieta, and Elisa Keller. 2021. "Capital Obsolescence and Agricultural Productivity." *The Quarterly Journal of Economics*, 136(1): 505–561.

Chamberlain, Gary. 1985. "1 : Heterogeneity, Omitted Variable Bias and Duration Dependence." In *Longitudinal Analysis of Labor Market Data. Econometric Society Monographs*, , ed. James J. Heckman and Burton S. Singer. Cambridge, England: Cambridge University Press.

Chari, V. V., and Hugo Hopenhayn. 1991. "Vintage Human Capital, Growth, and the Diffusion of New Technology." *Journal of Political Economy*, 99(6): 1142–1165.

Chay, Kenneth Y., Hilary Williamson Hoynes, and Dean Hyslop. 1999. "A Non-experimental Analysis of True State Dependence in Monthly Welfare Participation Sequences." *American Statistical Association*, 9–17.

Chernoff, Alex W. 2021. "Firm Heterogeneity, Technology Adoption and the Spatial Distribution of Population: Theory and Measurement." *Canadian Journal of Economics*, 54(2): 475–521.

Christensen, Clayton M. 1997. *The Innovator's Dilemma: When New Technologies Cause Great Firms to Fail.* Boston: Harvard Business Review Press.

Collard-Wexler, Allan, and Jan De Loecker. 2015. "Reallocation and Technology: Evidence from the US Steel Industry." *American Economic Review*, 105(1): 131–71.

Comin, Diego, and Bart Hobijn. 2010. "An Exploration of Technology Diffusion." *American Economic Review*, 100(5): 2031–2059.

Comin, Diego, and Marti Mestieri. 2014. "Technology Diffusion: Measurement, Causes, and Consequences." In *Handbook of Economic Growth.* Vol. 2, 565–622. Amsterdam: Elsevier.

Conley, Timothy G. 1999. "GMM Estimation with Cross Sectional Dependence." *Journal of Econometrics*, 92(1): 1–45.

Cooney, E.W. 1991. "Eighteenth Century Britain's Missing Sawmills: A Blessing in Disguise?" *Construction History*, 7: 29–46.

Coşar, A Kerem, Nezih Guner, and James Tybout. 2016. "Firm Dynamics, Job Turnover, and Wage Distributions in an Open Economy." *American Economic Review*, 106(3): 625–663.

Crafts, Nicholas. 2004. "Steam as a General Purpose Technology: A Growth Accounting Perspective." *The Economic Journal*, 114(495): 338–351.

Crafts, Nicholas F.R. 1977. "Industrial Revolution in England and France: Some Thoughts on the Question, 'Why Was England First?'." *The Economic History Review*, 30(3): 429–441.

Cronon, William. 2009. *Nature's Metropolis: Chicago and the Great West.* New York: W.W. Norton & Company.

Crouzet, Nicolas, Atin Gupta, and Filippo Mezzanotti. 2023. "Shocks and Technology Adoption: Evidence from Electronic Payment Systems." *Journal of Political Economy*, 131(11): 3003–3065.

Dano, Kevin. 2023. "Transition Probabilities and Moment Restrictions in Dynamic Fixed Effects Logit Models." arXiv Papers 2303.00083.

David, Paul A. 1985. "Clio and the Economics of QWERTY." *American Economic Review*, 75(2): 332–337.

David, Paul A. 1990. "The Dynamo and the Computer: An Historical Perspective on the Modern Productivity Paradox." *American Economic Review*, 80(2): 355–361.

David, Paul A., and Julie Ann Bunn. 1988. "The Economics of Gateway Technologies and Network Evolution: Lessons from Electricity Supply History." *Information Economics and Policy*, 3(2): 165–202.

Dedrick, Benjamin. 1931. "Plan and Power of a Flour Mill of Many Years Ago." *The Millers Review and Feed Forum*, XCV(2).

Denison, Edward F. 1964. "The Unimportance of the Embodied Question." *American Economic Review*, 54(2): 90–94.

Devine, Warren D. 1983. "From Shafts to Wires: Historical Perspective on Electrification." *The Journal of Economic History*, 43(2): 347–372.

Donaldson, Dave, and Richard Hornbeck. 2016. "Railroads and American Economic Growth: A "Market Access" Approach." *The Quarterly Journal of Economics*, 131(2): 799–858.

Dondlinger, Peter Tracy. 1919. *The Book of Wheat: An Economic History and Practical Manual of the Wheat Industry.* New York: Orange Judd Company.

Eckert, Fabian, and Michael Peters. 2023. "Spatial Structural Change." Working Paper.

Emery, Charles E. 1883. "The Cost of Steam Power." *Transactions of the American Society of Civil Engineers*, 12(1): 425–431.

Evans, Oliver. 1795. *The Young Mill-Wright and Miller's Guide.* Self-Published.

Farrell, Joseph, and Paul Klemperer. 2007. "Chapter 31: Coordination and Lock-In: Competition with Switching Costs and Network Effects." In . Vol. 3 of *Handbook of Industrial Organization*, , ed. M. Armstrong and R. Porter, 1967–2072. Amsterdam: Elsevier.

Feigenbaum, James. 2015. "Automated Census Record Linking: A Machine Learning Approach." Working Paper.

Feigenbaum, James, and Daniel Gross. 2024. "Organizational and Economic Obstacles to Automation: A Cautionary Tale from AT&T in the Twentieth Century." *Management Science*, 70(12): 8520–8540.

Felbermayr, Gabriel, Giammario Impullitti, and Julien Prat. 2018. "Firm Dynamics and Residual Inequality in Open Economies." *Journal of the European Economic Association*, 16(5): 1476–1539.

Feldman, Maryann P., and Dieter F. Kogler. 2010. "Stylized Facts in the Geography of Innovation." In *Handbook of the Economics of Innovation.* Vol. 1, , ed. Bronwyn H. Hall and Nathan Rosenberg, 381–410. Elsevier.

Fenichel, Allen H. 1966. "Growth and Diffusion of Power in Manufacturing, 1838–1919." In *Output, Employment, and Productivity in the United States after 1800.* , ed. Dorothy S. Brady, 443–478. Cambridge, MA: National Bureau of Economic Research.

Fernihough, Alan, and Kevin Hjortshøj O'Rourke. 2021. "Coal and the European Industrial

Revolution." *The Economic Journal*, 131(635): 1135–1149.

Ferrie, Joseph P. 1996. "A New Sample of Males Linked from the Public Use Microdata Sample of the 1850 US Federal Census of Population to the 1860 US Federal Census Manuscript Schedules." *Historical Methods: A Journal of Quantitative and Interdisciplinary History*, 29(4): 141–156.

Fisher, Redwood. 1845. "Advantages of Manufactories in the City of New York." *Fisher's National Magazine and Industrial Record*, 1(4): 358–362.

Floud, Roderick, and Deirdre Nansen McCloskey. 1981. *The Economic History of Britain since 1700.* Vol. 1, Cambridge, England: Cambridge University Press.

Flour and Feed. 1945. *Devoted to the Interests of the Flour and Feed Trade.* Vol. 22, Milwaukee, Wisconsin.

Frankel, Marvin. 1955. "Obsolescence and Technological Change in a Maturing Economy." *American Economic Review*, 45(3): 296–319.

Gerschenkron, Alexander. 1962. *Economic Backwardness in Historical Perspective.* Cambridge, MA: Belknap Press.

Gilchrist, Simon, and John C Williams. 2000. "Putty-Clay and Investment: A Business Cycle Analysis." *Journal of Political Economy*, 108(5): 928–960.

Giorcelli, Michela. 2019. "The Long-Term Effects of Management and Technology Transfers." *American Economic Review*, 109(1): 121–152.

Giroud, Xavier, Simone Lenzu, Quinn Maingi, and Holger Mueller. 2024. "Propagation and amplification of local productivity spillovers." *Econometrica*, 92(5): 1589–1619.

Gordon, Robert B. 1983. "Cost and Use of Water Power during Industrialization in New England and Great Britain: A Geological Interpretation." *Economic History Review*, 240–259.

Greenberg, Dolores. 1982. "Reassessing the Power Patterns of the Industrial Revolution: An Anglo-American Comparison." *The American Historical Review*, 87(5): 1237–1261.

Greenwood, Jeremy, Ananth Seshadri, and Mehmet Yorukoglu. 2005. "Engines of Liberation." *The Review of Economic Studies*, 72(1): 109–133.

Greenwood, Jeremy, and Mehmet Yorukoglu. 1997. "1974." *Carnegie-Rochester Conference Series on Public Policy*, 46: 49–95.

Griliches, Zvi. 1957. "Hybrid Corn: An Exploration in the Economics of Technological Change." *Econometrica*, 25(4): 501–522.

Guilfoos, T. 2025. "The evolution of the value of water power during the Industrial Revolution."

Habakkuk, Hrothgar John. 1967. *American and British Technology in the Nineteenth Century.* Cambridge, England: Cambridge University Press.

Haines, Michael R. 2010. "Historical, Demographic, Economic, and Social Data: The United States, 1790–2002." *ICPSR Volume 2896.*

Hall, Bronwyn H. 2004. "Innovation and Diffusion." National Bureau of Economic Research Working Paper Series 10212.

Halsey, Harlan I. 1981. "The choice between high-pressure and low-pressure steam power in America in the early nineteenth century." *The Journal of Economic History*, 41(4): 723–744.

Hanlon, W. Walker. 2022. "The Rise of the Engineer: Inventing the Professional Inventor during the Industrial Revolution." Working Paper.

Hansen, Gary D., and Edward C. Prescott. 2002. "Malthus to Solow." *American Economic Review*, 92(4): 1205–1217.

Henderson, Rebecca. 1995. "Of Life Cycles Real and Imaginary: The Unexpectedly Long Old Age of Optical Lithography." *Research Policy*, 24(4): 631–643.

Holmes, Thomas J., David K. Levine, and James A. Schmitz Jr. 2012. "Monopoly and the Incentive to Innovate when Adoption Involves Switchover Disruptions." *American Economic*

Journal: Microeconomics, 4(3): 1–33.
Hopenhayn, Hugo A. 1992. "Entry, Exit, and Firm Dynamics in Long Run Equilibrium." *Econometrica*, 60(5): 1127–1150.
Hornbeck, Richard, and Daniel Keniston. 2017. "Creative Destruction: Barriers to Urban Growth and the Great Boston Fire of 1872." *American Economic Review*, 107(6): 1365–1398.
Hornbeck, Richard, and Martin Rotemberg. 2024. "Growth Off the Rails: Aggregate Productivity Growth in Distorted Economies." *Journal of Political Economy*, 132(11): 3547–3602.
Hotz, V. Joseph, and Robert A. Miller. 1993. "Conditional Choice Probabilities and the Estimation of Dynamic Models." *The Review of Economic Studies*, 60(3): 497–529.
Howes, Anton. 2023. "How the Steam Engine Was Invented." *Age of Invention.*
Hsieh, Chang-Tai, and Peter J Klenow. 2009. "Misallocation and manufacturing TFP in China and India." *The Quarterly Journal of Economics*, 124(4): 1403–1448.
Huesler, Joel, and Eric Strobl. 2023. "The Creative-Destructive Force of Hurricanes: Evidence from Technological Adoption in Colonial Jamaican Sugar Estates?" Social Science Research Network Preprints.
Humlum, Anders. 2022. "Robot Adoption and Labor Market Dynamics." Working Paper.
Humlum, Anders, and Emilie Vestergaard. 2025. "The Unequal Adoption of ChatGPT Exacerbates Existing Inequalities among Workers." *Proceedings of the National Academy of Sciences*, 122(1): e2414972121.
Hunter, Louis C. 1979. *A History of Industrial Power in the United States, 1780-1930.* Vol. 1: Waterpower in the Century of the Steam Engine, Charlottesville, VA: University Press of Virginia.
Hunter, Louis C. 1985. *A History of Industrial Power in the United States, 1780-1930.* Vol. 2: Steam Power, Charlottesville, VA: University Press of Virginia.
Huntington, Heather, Brenda Samaniego dela Parra, and Ajay Shenoy. 2023. "Measuring and Estimating Retail Productivity." Working Paper.
Jaremski, Matthew. 2014. "National Banking's Role in US Industrialization, 1850–1900." *The Journal of Economic History*, 74(1): 109–140.
Jovanovic, Boyan, and Glenn M. MacDonald. 1994. "Competitive Diffusion." *Journal of Political Economy*, 102(1): 24–52.
Jovanovic, Boyan, and Peter L. Rousseau. 2005. "General Purpose Technologies." In *Handbook of Economic Growth*. Vol. 1, , ed. Philippe Aghion and Steven N. Durlauf, 1181–1224. Amsterdam: Elsevier.
Jovanovic, Boyan, and Saul Lach. 1989. "Entry, Exit, and Diffusion with Learning by Doing." *American Economic Review*, 79(4): 690–699.
Jovanovic, Boyan, and Yaw Nyarko. 1996. "Learning by Doing and the Choice of Technology." *Econometrica*, 64(6): 1299–1310.
Jovanovic, Boyan, and Yuri Yatsenko. 2012. "Investment in Vintage Capital." *Journal of Economic Theory*, 147(2): 551–569.
Juhász, Réka, Mara P. Squicciarini, and Nico Voigtländer. 2024. "Technology Adoption and Productivity Growth: Evidence from Industrialization in France." *Journal of Political Economy*, 132(10): 3215–3259.
Kuhlmann, Charles Byron. 1929. *The Development of the Flour-Milling Industry in the United States: With Special Reference to the Industry in Minneapolis.* Boston: Houghton Mifflin.
Lancaster, Tony, and Stephen Nickell. 1980. "The Analysis of Re-employment Probabilities for the Unemployed." *Journal of the Royal Statistical Society, Series A: Statistics in Society*, 143(2): 141–152.
Le Bris, David, William N Goetzmann, and Sébastien Pouget. 2019. "The Present Value

Relation over Six Centuries: The Case of the Bazacle Company." *Journal of Financial Economics*, 132(1): 248–265.

Lu, Yao, Gordon M Phillips, and Jia Yang. 2023. "The Impact of Cloud Computing and AI on Industry Dynamics and Competition." Social Science Research Network, Tuck School of Business at Dartmouth Research Paper Series 4480570.

Main, Chas, et al. 1890. "Cost of Steam and Water Power." *Journal of Fluids Engineering*, 11: 108–120.

Manning, Charles H. 1889. "Comparative Cost of steam and water power." *Journal of Fluids Engineering*, 10: 499–505.

Mayr, Otto. 1975. "Yankee Practice and Engineering Theory: Charles T. Porter and the Dynamics of the High-Speed Steam Engine." *Technology and Culture*, 16(4): 570–602.

Melitz, Marc J. 2003. "The Impact of Trade on Intra-industry Reallocations and Aggregate Industry Productivity." *Econometrica*, 71(6): 1695–1725.

Mian, Atif, and Amir Sufi. 2014. "What Explains the 2007–2009 Drop in Employment?" *Econometrica*, 82(6): 2197–2223.

Miller, Nathan, Matthew Osborne, Gloria Sheu, and Gretchen Sileo. 2022. "Technology and Market Power: The United States Cement Industry, 1974-2019." Georgetown McDonough School of Business Research Paper 4041168.

Mokyr, Joel. 2016. *A Culture of Growth: The Origins of the Modern Economy.* Princeton, NJ: Princeton University Press.

Monroe, James. 1825. "Message from the President of the United States, Transmitting a Report of the Commissioners Appointed under the Act of the Third of March, 1823, to Establish a National Armory on the Western Waters."

Montgomery, James. 1840. *A Practical Detail of the Cotton Manufacture of the United States of America: And the State of the Cotton Manufacture of That Country Contrasted and Compared with That of Great Britain; With Comparative Estimates of the Cost of Manufacturing in Both Countries.* Glasgow: J. Niven.

Mullin, John R, and Zenia Kotval. 2021. "Manufacturing in Puritan Rural Towns in New England 1630–60:'A Miller Never Goes to Heaven'." *Rural History*, 32(2): 187–196.

National Industrial Conference Board. 1925. "Trade Associations: Their Economic Significance and Legal Status." National Industrial Conference Board, Incorporated.

Nurkse, Ragnar. 1953. *Problems of Capital Formation in Underdeveloped Countries.* Oxford: Basil Blackwell.

Olmstead, Alan L, and Paul W Rhode. 2001. "Reshaping the Landscape: The Impact and Diffusion of the Tractor in American Agriculture, 1910–1960." *The Journal of Economic History*, 61(3): 663–698.

Ottonello, Pablo, and Thomas Winberry. 2020. "Financial Heterogeneity and the Investment Channel of Monetary Policy." *Econometrica*, 88(6): 2473–2502.

Parente, Stephen L. 1994. "Technology Adoption, Learning-by-Doing, and Economic Growth." *Journal of Economic Theory*, 63(2): 346–369.

Parente, Stephen L., and Edward C. Prescott. 1994. "Barriers to Technology Adoption and Development." *Journal of Political Economy*, 102(2): 298–321.

Perren, Richard. 1990. "Structural Change and Market Growth in the Food Industry: Flour Milling in Britain, Europe, and America, 1850-1914." *Economic History Review*, 43(3): 420–437.

Porter, Charles T. 1868. "On the Allen Engine and Governor." *Proceedings of the Institution of Mechanical Engineers*, 19(1): 50–80.

Price, Joseph, Kasey Buckles, Jacob Van Leeuwen, and Isaac Riley. 2021. "Combining

Family History and Machine Learning to Link Historical Records: The Census Tree Data Set." *Explorations in Economic History*, 80: 101391.

Reichardt, Hugo. 2024. "Scale-Biased Technical Change and Inequality." *Working Paper*.

Riley, Shawn J., Stephen D. DeGloria, and Robert Elliot. 1999. "Index That Quantifies Topographic Heterogeneity." *Intermountain Journal of Sciences*, 5(1-4): 23–27.

Rosenberg, Nathan, and Manuel Trajtenberg. 2004. "A General-Purpose Technology at Work: The Corliss Steam Engine in the Late-Nineteenth-Century United States." *The Journal of Economic History*, 64(1): 61–99.

Ruggles, Steven, Catherine A. Fitch, and Evan Roberts. 2018. "Historical Census Record Linkage." *Annual Review of Sociology*, 44: 19–37.

Rust, John. 1987. "Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher." *Econometrica: Journal of the Econometric Society*, 999–1033.

Salter, Wilfred Edward Graham. 1960. *Productivity and Technical Change.* Cambridge, England: Cambridge University Press.

Saxonhouse, Gary, and Gavin Wright. 1987. "Stubborn Mules and Vertical Integration: The Disappearing Constraint?" *Economic History Review*, 40(1): 87–94.

Schaal, Edouard. 2017. "Uncertainty and Unemployment." *Econometrica*, 85(6): 1675–1721.

Schenck, J.S., and William S. Rann. 1887. *History of Warren County, Pennsylvania: With Illustrations and Biographical Sketches of Some of Its Prominent Men and Pioneers.* Syracuse, NY: D. Mason & Company.

Schumpeter, Joseph A. 1942. *Capitalism, Socialism and Democracy.* New York: Harper & Brothers.

Scientific American. 1869. "Improvements in the Steam Engine." 20(23): 361.

Scientific American. 1870. "The Allen Engine." 23(24): 374.

Scientific American. 1871. "Statistics of Steam Boiler Explosions for the Year 1870." 24(10): 153.

Scientific American. 1881. "Whose Boilers Explode." 44(12): 176.

Sedláček, Petr, and Vincent Sterk. 2017. "The Growth Potential of Startups over the Business Cycle." *American Economic Review*, 107(10): 3182–3210.

Sharrer, G. Terry. 1982. "The Merchant-Millers: Baltimore's Flour Milling Industry, 1783-1860." *Agricultural History*, 56(1): 138–150.

Smil, Vaclav. 2014. "The Long Slow Rise of Solar and Wind." *Scientific American*, 310(1): 52–57.

Snow, Daniel. 2004. "Extraordinary Efficiency Growth in Response to New Technology Entries: The Carburetor's "Last Gasp"'." *Academy of Management Proceedings*, 2004(1): K1–K6.

Solow, Robert M. 1962. "Technical Progress, Capital Formation, and Economic Growth." *American Economic Review*, 52(2): 76–86.

Stokey, Nancy L., Robert E. Lucas, and Edward C. Prescott. 1989. *Recursive Methods in Economic Dynamics.* Cambridge, MA: Harvard University Press.

Strassmann, W Paul. 1959. "Creative Destruction and Partial Obsolescence in American Economic Development." *The Journal of Economic History*, 19(3): 335–349.

Swain, George F. 1888. "Statistics of Water Power Employed in Manufacturing in the United States." *Publications of the American Statistical Association*, 1(1): 5–36.

Tauchen, George. 1986. "Finite State Markov-Chain Approximations to Univariate and Vector Autoregressions." *Economics Letters*, 20(2): 177–181.

Temin, Peter. 1966. "Steam and Waterpower in the Early Nineteenth Century." *The Journal of Economic History*, 26(2): 187–205.

Thurston, Robert Henry. 1878. *A History of the Growth of the Steam-Engine.* Vol. 24, New York: D. Appleton.

Traiberman, Sharon. 2019. "Occupations and import competition: Evidence from Denmark." *American Economic Review*, 109(12): 4260–4301.

Treasury Department. 1838. *Steam Engines: Letter from the Secretary of the Treasury, Transmitting, in Obedience to a Resolution of the House, of the 29Th of June Last, Information in Relation to Steam Engines, &c. (The 'Woodbury Report').* 25th Congress.

United States Census Bureau. 2021. "County Business Patterns." *U.S. Department of Commerce.*

United States Census Office. 1850. "Manufacturers of the United States in 1850." *U.S. Department of the Interior.*

United States Census Office. 1860. "Manufacturers of the United States in 1860." *U.S. Department of the Interior.*

United States Census Office. 1870. "Manufacturers of the United States in 1860." *U.S. Department of the Interior.*

United States Census Office. 1880. "Manufacturers of the United States in 1860." *U.S. Department of the Interior.*

United States Census Office. 1883. "Tenth Census. Volumes 16 & 17. Reports on the Water Power of the United States." *U.S. Department of the Interior.*

United States Congress, House of Representatives. 1833. *House Documents, Otherwise Publ. as Executive Documents: 13th Congress, 2d Session-49th Congress, 1st Session (The 'McLane Report'). United States congressional serial set.*

Veblen, T. 1915. *Imperial Germany and the Industrial Revolution. Imperial Germany and the Industrial Revolution*, New York: Macmillan.

Verhoogen, Eric. 2023. "Firm-Level Upgrading in Developing Countries." *Journal of Economic Literature*, 61(4): 1410–64.

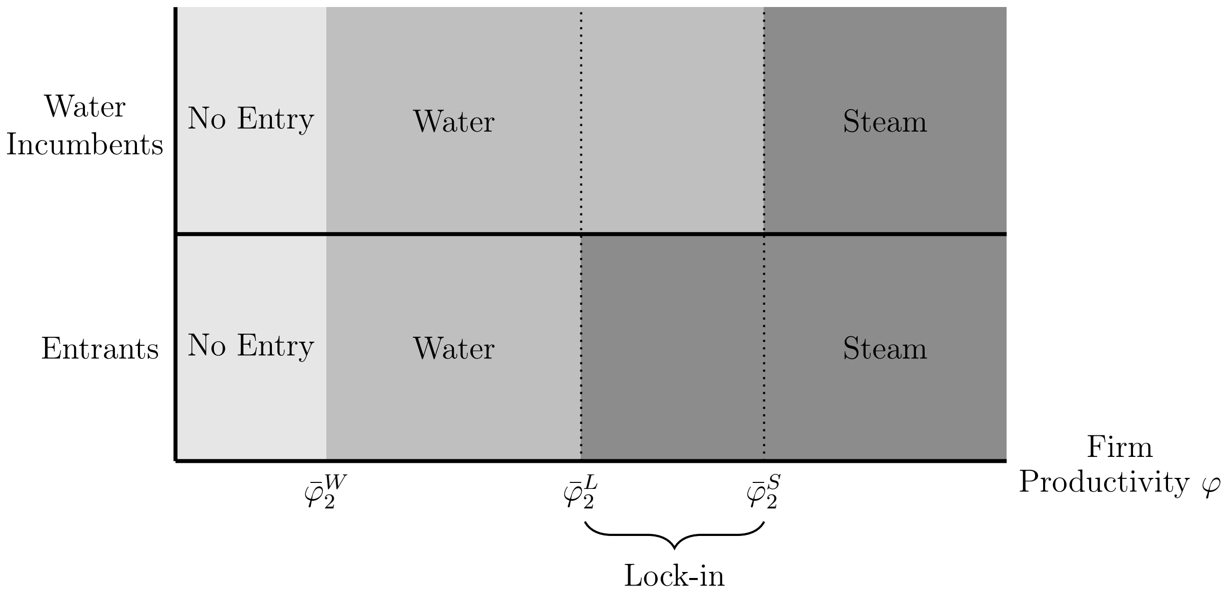
Weeden, William Babcock. 1890. *Economic and Social History of New England, 1620-1789.* Vol. 1, Houghton, Mifflin.

Westworth, OA. 1932. "The Albion steam flour mill." *Economic History*, 2(7): 380–395.

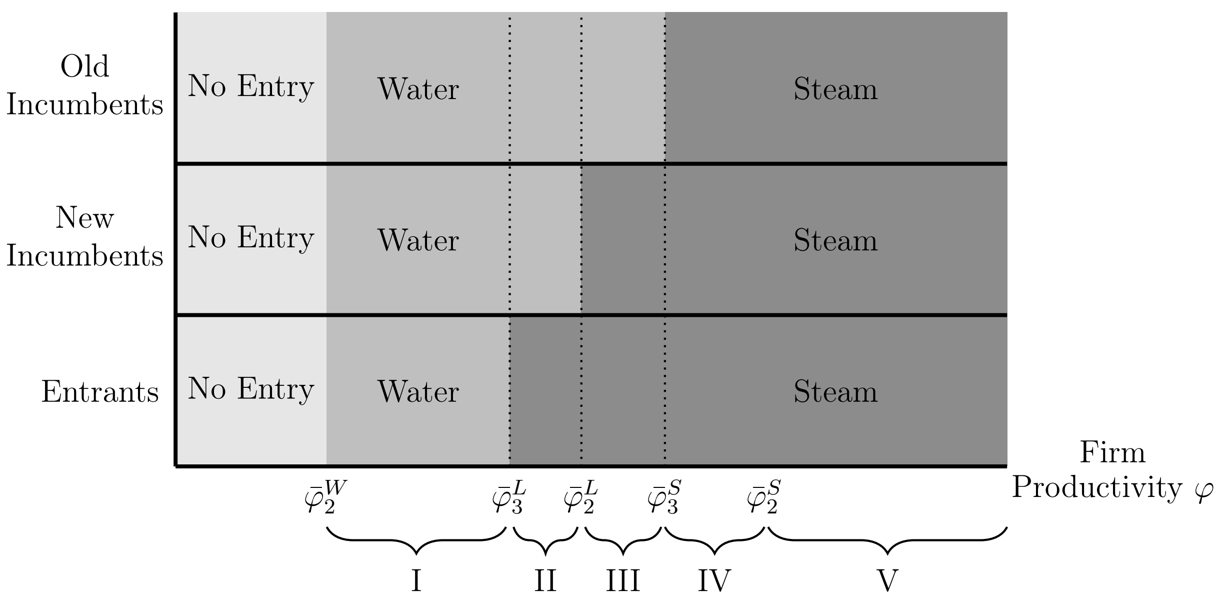
Wrigley, E. A. 2010. *Energy and the English Industrial Revolution.* Cambridge, England: Cambridge University Press.

Figure 1. Technology Productivity Cutoffs

Panel A. Period 2



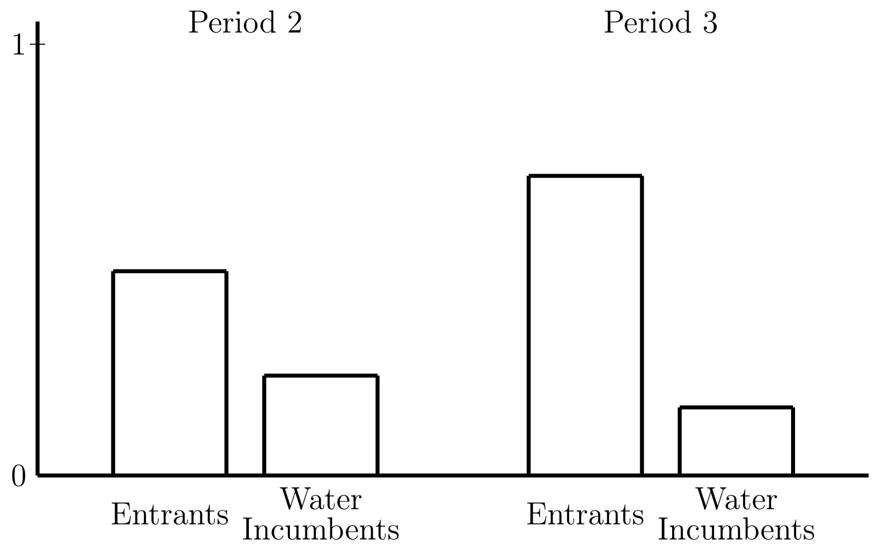
Panel B. Period 3



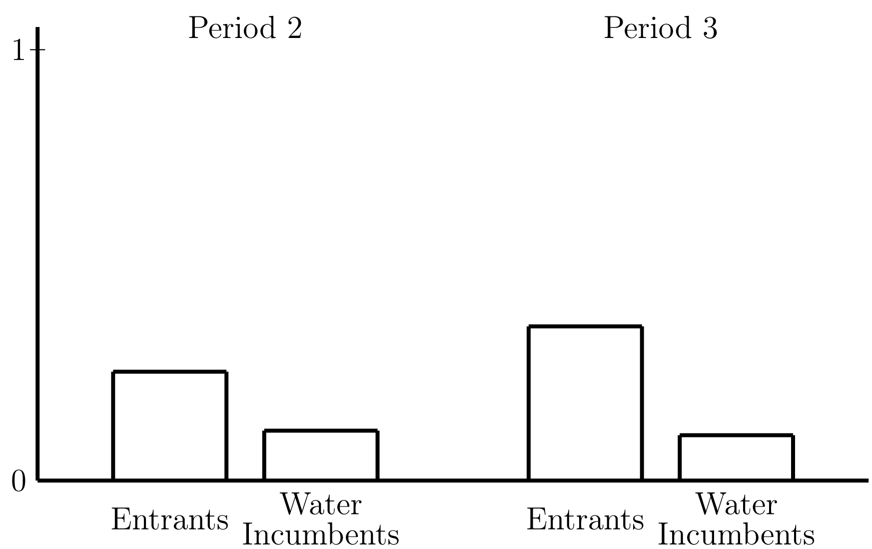
Notes: This figure visualizes the productivity cutoffs for technology use among mills. In the first period, all mills with $\varphi_j \geq \bar{\varphi}_1^W$ use water. All mills adopt steam power when they have high enough productivity ($\varphi_j \geq \bar{\varphi}_2^S$). At slightly lower productivity, entrants use steam and incumbents stay with water, creating a "lock-in" region for incumbents. Brackets at the bottom of the figure highlight five subregions of productivity when comparing periods 2 and 3. Appendix D.1 presents an analytical solution for the productivity cutoffs and describes the parameter values used in the illustration shown in this plot.

Figure 2. Steam Adoption in the Stylized Model

Panel A. Steam Adoption Share



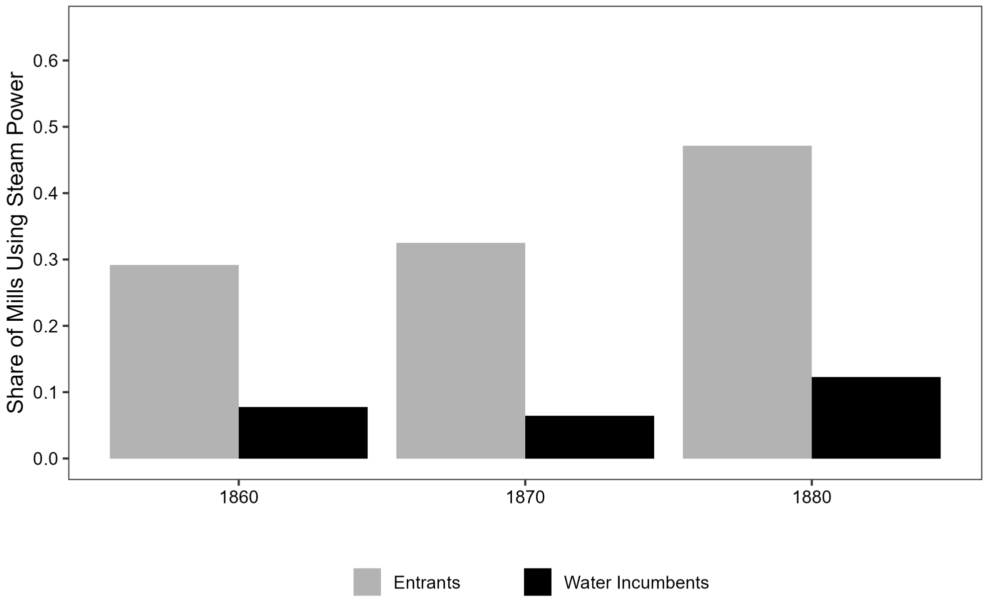
Panel B. Difference in Steam Adoption Share (in Lower WPP Counties)



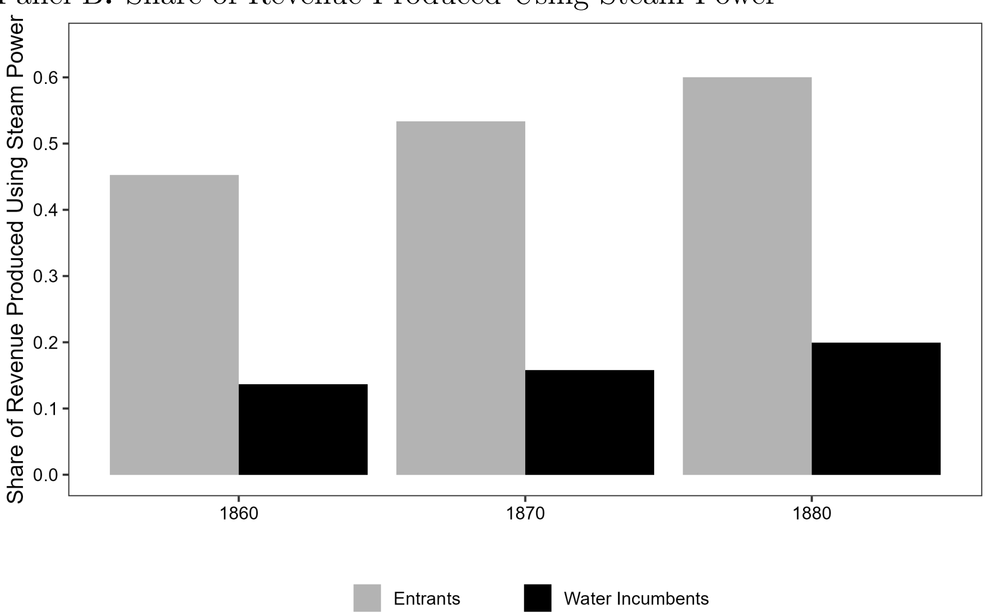
Notes: Panel A compares the steam adoption share among entrants to the lower share of water incumbents that switch to steam in periods 2 and 3. Panel B shows that in places with lower waterpower potential, entrants are more likely to adopt steam and incumbents are only moderately more likely to switch to steam. Appendix D.1 presents an analytical solution for the productivity cutoffs and describes the parameter values used in the illustration shown in this plot.

Figure 3. Steam-Use Share, for Entrants and Water Incumbents

Panel A. Share of Mills Using Steam Power

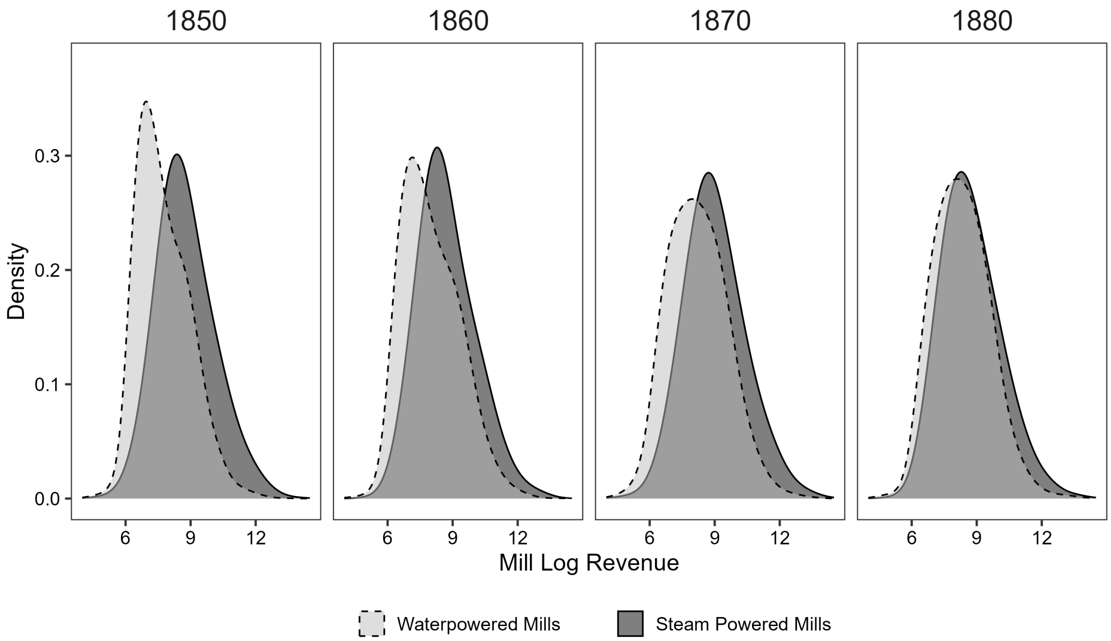


Panel B. Share of Revenue Produced Using Steam Power



Notes: This figure shows steam-use rates, by mill type ("Entrants" and "Water Incumbents"). Entrants began operations after the prior Census. Water Incumbents used water power in the prior Census. Panel A shows the share of mills using steam power, for each mill type. Panel B shows the share of revenue produced using steam power, for each mill type. Data from our main sample (Figure 5), using our digitized establishment-level Census of Manufactures (1850-1880).

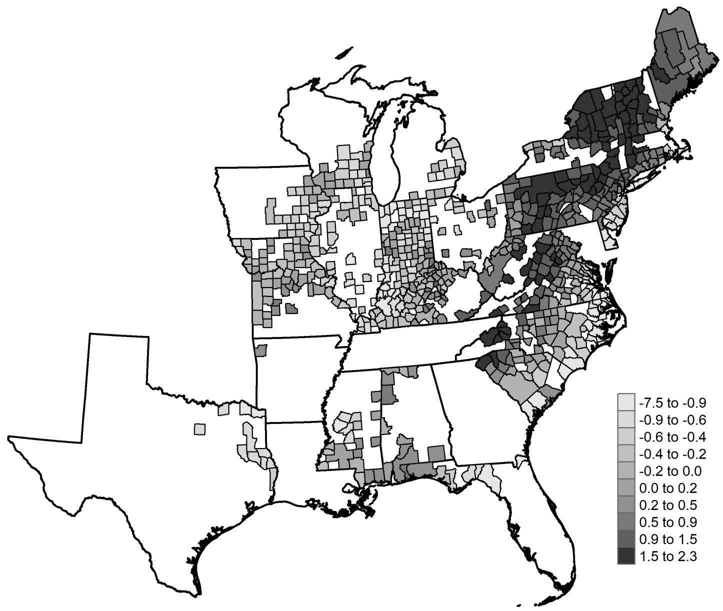
Figure 4. Mill Size Distribution, by Power Source



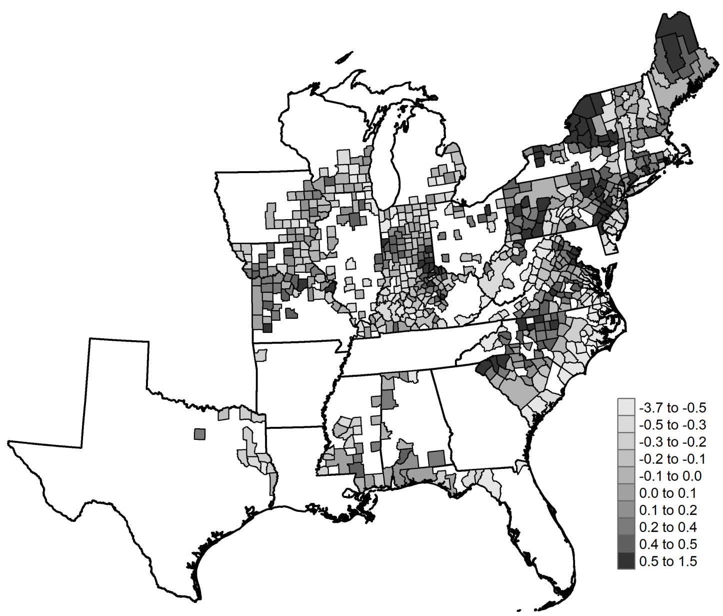
Notes: This figure shows the distribution of mill revenue, by power source, in each decade. Data from our main sample (Figure 5), using our digitized establishment-level Census of Manufactures (1850-1880).

Figure 5. County Waterpower Potential, Measured and Residualized

Panel A. County Waterpower Potential, Measured

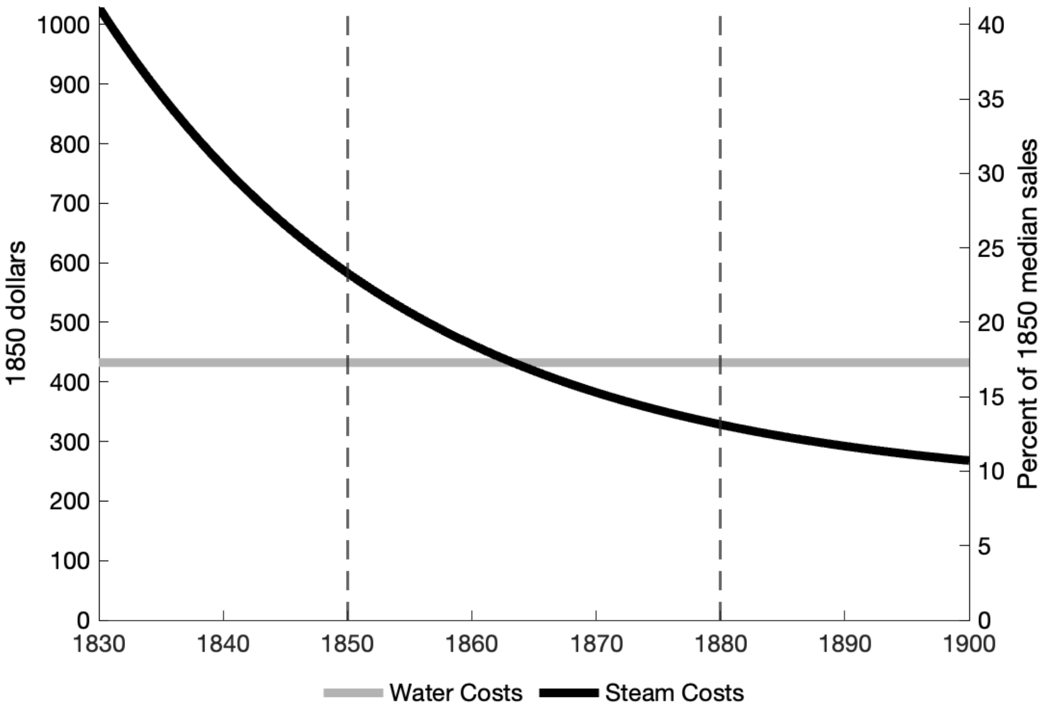


Panel B. County Waterpower Potential, Residualized



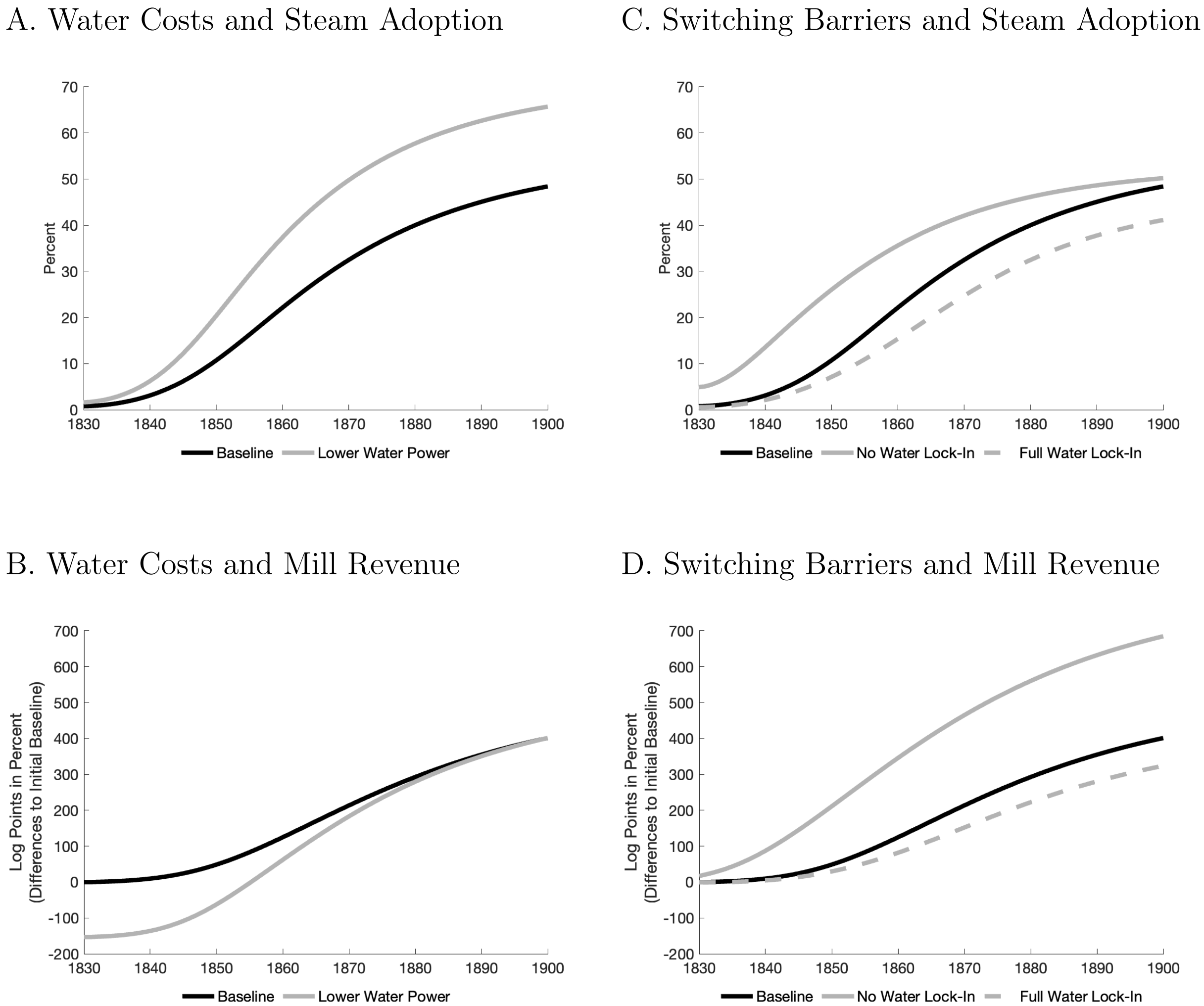
Notes: This figure shows county waterpower potential, with darker shares corresponding to greater waterpower potential deciles. The sample is restricted to our main balanced panel of 689 counties. Panel A shows our measure of county waterpower potential: the sum of flow rate × fall height across all river segments per square mile (standardized to standard deviations). Panel B shows the residual county waterpower potential, after controlling for our main baseline controls: total county water flow and terrain ruggedness; the presence of a navigable waterway, distance to the nearest navigable waterway, and county market access in 1850; the presence of coal in the county, the share of county area covered by coal deposits, and access to coal deposits. Data from NHDPlusV2.

Figure 6. Water and Steam Adoption Costs: Structural Estimates



Notes: This figure plots our structural estimates of the adoption costs of water $c_B(W)$ and steam power $c_t(S)$, estimated in Table 7. The right axis is in percent of 1850 median firm sales, which the left axis converts to 1850 dollars using median firm sales in our 1850 data.

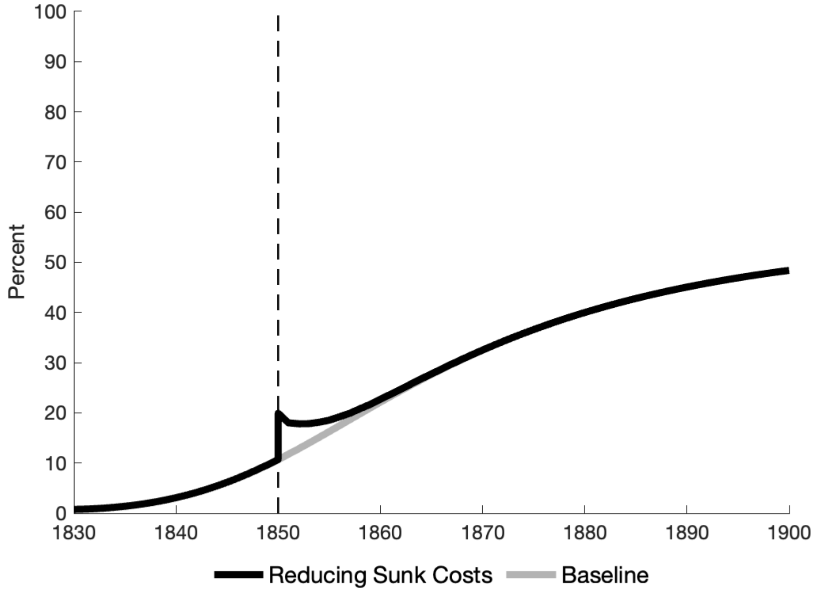
Figure 7. Water Technology and the Impacts of Steam Power



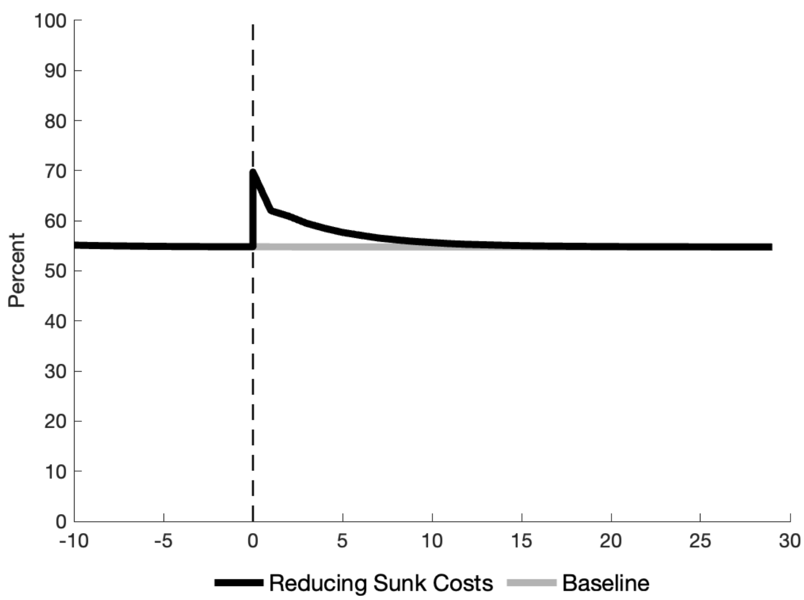
Notes: This figure shows the share of steam users and total mill revenue in model counties with different waterpower availability. Mill revenue is measured in log differences to the initial steady state of the baseline region. Panels A and B plot the average county (black line) and a region with one standard deviation lower waterpower potential (gray line), where the only parameter difference between the regions is the fixed cost of water power adoption. Panels C and D plot the impacts of switching barriers. The black line shows adoption for our baseline estimates, the gray line removes switching barriers ($\omega^W = 1, c(W,S) = 0$), and the dashed line represents prohibitive switching barriers ($c(W,S) \to \infty$).

Figure 8. Steam Adoption in Response to Reducing Sunk Costs

A. During the Technology Transition (Year 1850)

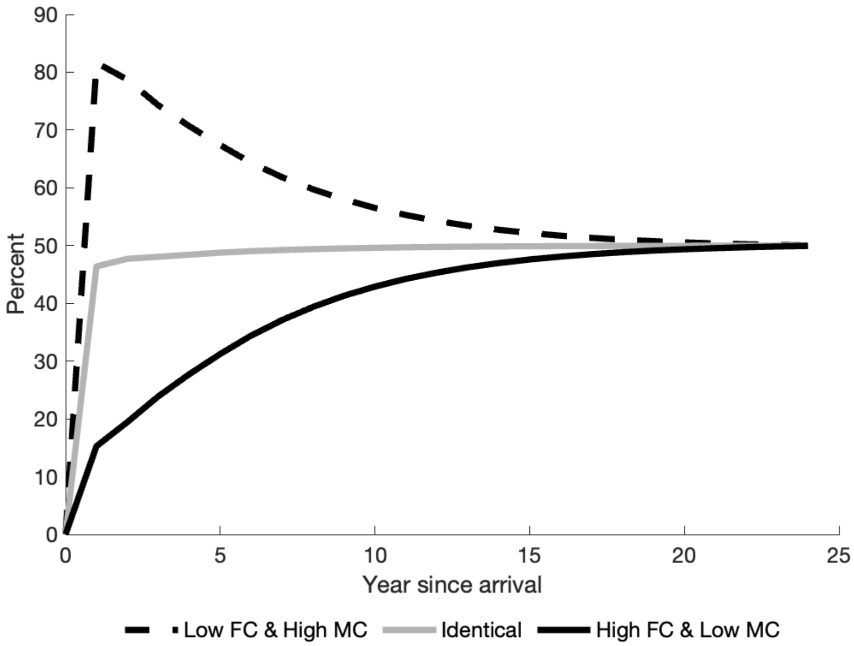


B. In Steady State



Notes: This figure shows how steam adoption responds to a counterfactual shock that temporarily reduces the sunk cost to switching. Panel A shows the impact in 1850, during the transition. Panel B shows the impact of the shock in the terminal steady state. Both panels compare counterfactual adoption of steam power (in black) to the factual adoption (in gray).

Figure 9. Technology Adoption and Fixed vs Marginal Costs



Notes: This figure simulates the adoption of new technologies under different scenarios. One technology ("High FC & low MC") has a marginal cost advantage equal to our estimate of steam's marginal cost advantage over water in 1900, while the other technology ("Low FC & high MC") has a lower fixed cost, chosen such that in an economy with both, the steady-state adoption rate of each is 50%. Otherwise the technologies have the same parameters as those we estimate for water power. For comparison, the gray line shows the adoption speed when introducing a new technology in an environment that already has its equivalent (so the old and new technologies are identical other than through idiosyncratic shocks). The black line shows the slow adoption of technology 1 ("High FC & low MC") in an environment that already has technology 2 ("Low FC & high MC"). The dashed line shows the fast adoption of technology 2 ("Low FC & high MC") in an environment that already has technology 1 ("High FC & low MC"), despite there being switching costs from sunk investment. The x-axis is years (the new technology is introduced in year 1), and the y-axis is the percent of establishments using the new technology.

Table 1. Composition of Milling

	Share of Total Milling					Share of Steam Milling		
	Steam Entrants (1)	Water Entrants (2)	Steam Incumbents (3)	Water Incumbents (Switchers) (4)	Water Incumbents (Stayers) (5)	Entrants (6)	Steam Incumbents (7)	Water Incumbents (8)
Panel A. Establishments								
1860	0.23	0.56	0.01	0.01	0.18	0.90	0.05	0.06
1870	0.28	0.58	0.03	0.01	0.11	0.90	0.07	0.03
1880	0.37	0.41	0.06	0.02	0.14	0.84	0.11	0.05
Panel B. Revenue								
1860	0.36	0.43	0.04	0.02	0.15	0.85	0.09	0.06
1870	0.44	0.38	0.07	0.02	0.09	0.85	0.12	0.03
1880	0.44	0.29	0.10	0.04	0.14	0.77	0.17	0.06

Notes: Columns 1–5, in Panel A, show the share of total mills that are steam entrants, water entrants, steam incumbents, or water incumbents (distinguishing between those who switched to steam and those who stayed with water power). Columns 6–8 show the share of steam mills in each decade that are steam entrants, steam incumbents, or water incumbents. Panel B reports corresponding numbers for the share of total revenue produced by each mill type. Data from our main sample (Figure 5), using our digitized establishment-level Census of Manufactures (1850-1880).

Table 2. Survival Rates, by Revenue and Power Source

	Survival Rate					
	By Revenue Quartile				By Power Source	
	Q1 (1)	Q2 (2)	Q3 (3)	Q4 (4)	Water (5)	Steam (6)
From 1850 to 1860	0.168	0.201	0.206	0.231	0.209	0.140
From 1860 to 1870	0.167	0.187	0.197	0.218	0.213	0.134
From 1870 to 1880	0.190	0.224	0.260	0.275	0.256	0.195

Notes: This table shows the measured survival rate of mills, by decade. Columns 1-4 report the share of all mills that survive in each decade by the revenue quartile of their initial year, column 5 reports survival for water powered mills, and column 6 reports survival for steam powered mills. We denote a mill as surviving if we can find a record for it in the subsequent Census.

Data from our main sample counties (Figure 5), using our digitized establishment-level Census of Manufactures (1850-1880).

Table 3. Mill Activity in 1850, by County Waterpower Potential

	All Mills (1)	Only Lumber Mills (2)	Only Flour Mills (3)
Panel A. Number of Waterpowered Mills			
Lower Waterpower	-1.059	-1.257	-0.780
	(0.130)	(0.173)	(0.109)
Panel B. Revenue of Waterpowered Mills			
Lower Waterpower	-1.133	-1.025	-1.167
	(0.249)	(0.222)	(0.300)
Panel C. Steam Share of Mills			
Lower Waterpower	0.089	0.109	0.055
	(0.015)	(0.019)	(0.016)
Panel D. Steam Share of Revenue			
Lower Waterpower	0.127	0.170	0.057
	(0.023)	(0.032)	(0.021)
Panel E. Total Number of Mills			
Lower Waterpower	-0.960	-1.109	-0.737
	(0.119)	(0.156)	(0.105)
Panel F. Total Revenue of Mills			
Lower Waterpower	-0.881	-0.717	-0.971
	(0.215)	(0.171)	(0.291)
# County-Industries	1,199	613	586

Notes: This table shows the relationship between mill activity in 1850 and county waterpower potential. "Lower Waterpower" is a negative standardized measure of county water power potential, with standard deviation of one, so the estimates reflect differences in counties with one standard deviation lower waterpower potential.

Each panel shows the effect of water power potential on a different outcome in 1850: the total number of water powered mills (Panel A); the total revenue of water powered mills (Panel B); the share of mills using steam power (Panel C); the share of milling revenue from using steam power (Panel D); the total number of mills (Panel E); and total mill revenue (Panel F). Column 1 reports pooled estimates from county-industry regressions, for lumber and flour milling; Column 2 restricts the sample to lumber mills only; and Column 3 restricts the sample to flour mills only. Panels A, B, E, and F use PPML estimation, which approximates percent differences. Panels C and D are OLS regressions, weighting county-industries by their number of mills, which reflect percentage point differences in the shares.

All regressions include industry fixed effects and our baseline controls interacted with industry: an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850; an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network.

Each observation is a county-industry in 1850. Robust standard errors clustered by county are reported in parentheses. Data from our main sample counties (Figure 5), using our digitized establishment-level Census of Manufactures (1850) and NHDPlusV2.

Table 4. Steam Adoption and Mill Growth, by County Waterpower Potential

	Steam Share of Mills (1)	Total Mills (2)	Total Mill Revenue (3)
Growth in Lower Waterpower Counties:			
From 1850 to 1860	0.068	0.223	0.210
	(0.017)	(0.061)	(0.080)
# County-Industries	1,084	1,199	1,199
From 1860 to 1870	0.032	0.106	0.178
	(0.014)	(0.052)	(0.097)
# County-Industries	1,060	1,199	1,199
From 1870 to 1880	-0.010	0.116	0.165
	(0.014)	(0.034)	(0.084)
# County-Industries	1,141	1,199	1,199

Notes: This table shows the relationship between growth in mill activity and county waterpower potential. "Lower Waterpower" is a negative standardized measure of county water power potential, with standard deviation of one, so the estimates reflect differences in counties with one standard deviation lower waterpower potential.

The outcomes are the share of mills using steam power (column 1), the total number of mills (column 2), and total mill revenue (column 3). Each row corresponds to growth over the indicated decade, using only data from the indicated years.

Column 1 reports OLS estimates, restricting the sample to county-industries with at least one mill in both decades (for the steam share to be defined) and weighting by the number of mills in that county-industry in 1850. These estimates reflect percentage point differences in the shares. Columns 2 and 3 report PPML estimates for a balanced panel of county-industries (including zeros), which approximate percent differences.

All regressions include county-industry fixed effects, industry-year fixed effects, and our baseline controls interacted with industry and year: an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850; an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network.

Each observation is a county-industry-year. Robust standard errors clustered by county are reported in parentheses. Data from our main sample counties (Figure 5), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Table 5. Entry Rates and Survival Rates, by County Waterpower Potential

	Entry Rate (1)	Survival Rate (2)	Difference (1) − (2) (3)
Elasticity with Respect to Lower Waterpower:			
In 1860	0.328	-0.237	0.565
	(0.074)	(0.065)	(0.090)
# County-Industries	1,199	1,199	
In 1870	0.161	-0.276	0.438
	(0.059)	(0.058)	(0.074)
# County-Industries	1,199	1,199	
In 1880	0.189	-0.156	0.345
	(0.043)	(0.040)	(0.060)
# County-Industries	1,199	1,199	

Notes: This table shows the elasticity of mill entry and mill survival, over the previous decade, with respect to county waterpower potential. "Lower Waterpower" is a negative standardized measure of county waterpower potential, with standard deviation of one, so the estimates reflect differences in counties with one standard deviation lower waterpower potential.

Column 1 reports results for entry, column 2 reports results for incumbent survival, and column 3 reports the difference in these estimates. Each row corresponds to a different PPML regression, using data from the indicated Census year and previous Census year, which approximates percent differences in the rates.

All regressions include county-industry fixed effects, industry-year fixed effects, and our baseline controls interacted with industry and year: an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850; an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network.

Each observation is a county-industry-year. Robust standard errors clustered by county are reported in parentheses. Data from our main sample counties (Figure 5), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Table 6. Steam Adoption Shares for Entrants and Water Incumbents, by County Waterpower Potential

	Entrants (1)	Water Incumbents (2)	Difference (1) − (2) (3)	New Water Incumbents (4)	Difference (1) − (4) (5)
Adoption in Lower Waterpower Counties:					
In 1860	0.166	0.034	0.132		
	(0.024)	(0.022)	(0.024)	-	-
# County-Industries	1,075	609			
In 1870	0.187	0.051	0.136	0.046	0.141
	(0.022)	(0.018)	(0.025)	(0.022)	(0.028)
# County-Industries	1,153	559		499	
In 1880	0.171	0.047	0.124	0.054	0.116
	(0.022)	(0.024)	(0.026)	(0.028)	(0.030)
# County-Industries	1,171	686		651	

Notes: This table shows the relationship between county waterpower potential and the steam use of entrant mills and water incumbent mills. "Lower Waterpower" is a negative standardized measure of county waterpower potential, with standard deviation of one, so the estimates reflect differences in counties with one standard deviation lower waterpower potential.

The outcome in column 1 is the share of entrants using steam power, restricted to county-industries with at least one entrant in that year. Column 2 reports the share of "water incumbents" (mills that used water power in the previous Census year) who switched to steam power. For column 2, the sample is restricted to county-industries with at least one surviving water incumbent. Column 3 reports the difference between the estimates in columns 1 and 2. Each row corresponds to a different OLS regression, using data from the indicated Census year only, which reports percentage point differences in the shares. Column 4 reports the share of "new water incumbents" (mills that used water power in the previous Census year, but were inactive before that year) who switched to steam power. For column 4, the sample is restricted to county-industries with at least one surviving water incumbent. Column 5 reports the difference between columns 1 and 4.

All regressions include industry fixed effects and our baseline controls interacted with industry: an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850; an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network.

For each row, each observation is a county-industry, weighted by the number of mills in 1850. Robust standard errors clustered by county are reported in parentheses. Data from our main sample counties (Figure 5), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Table 7. Parameter Estimates

Parameter	Description	Value	Dollars	Source
Panel A. Power Costs				
$c(W, S)$	Residual switching costs from water	0.014	34	Table A.1
$c(S, W)$	Residual switching costs from steam	0.055	137	Table A.1
$c_S^{(initial)}$	Steam cost (initial)	0.412	1029	Table A.1
$c_S^{(terminal)}$	Steam cost (terminal)	0.087	219	Table A.1
$c_S^{(slope)}$	Steam cost (time-slope)	0.040		Section D.3.3.3
$c_B(W)$	Water cost in baseline county	0.173	433	Table A.1
$c_L(W)$	Water cost in lower water power county	0.211	528	Table A.1
κ	Agglomeration in steam adoption	0.016	41	Table A.1
ρ	Dispersion in power costs	0.061	151	Table A.1
Panel B. Entry and Operating Costs				
f_e	Entry costs	0.004	10	Table A.1
f_o^E	Startup cost	0.260	649	Table A.1
f_o^W	Operating cost of water user	0.107	269	Table A.1
f_o^S	Operating cost of steam user	0.303	757	Table A.1
ρ_o	Dispersion in operating costs	0.061	151	Table A.1
Panel C. Productivity				
γ	Steam productivity premium	0.089		Table A.1
π	Autocorrelation in baseline productivities	0.968		Table A.1
σ	Dispersion in baseline productivities	0.090		Table A.1
α	Agglomeration in steam production	0.025		Table A.1
Panel D. Demand				
ϵ	Elasticity of firm demand	6.000		Section D.3.3.3
η	Elasticity of local demand	5.900		Table A.1
Panel E. Other Parameters				
β	Water share in startup cost	0.400		Section D.3.3.3
ω	Power resale value	0.000		Section D.3.3.3
δ	Discount factor	0.940		Section D.3.3.3

Notes: This table shows the estimated values of our model parameters and their sources of identification. Columns 1 and 2 list each parameter and its description. Column 3 reports the parameter values. Panel A includes the parameters of power adoption costs, Panel B includes the parameters of entry and operating costs, Panel C includes the production technology parameters, Panel D includes the parameters of product demand, and Panel E includes other calibrated parameters. Parameter values in Panels A and B are in units of 1850 median firm sales, while Panels C, D, and E are unit-free elasticities unless otherwise noted. Parameters with Table A.1 as their sources are directly estimated, with the other parameters calibrated in Section D.3.3.3.

Table 8. Aggregate Inefficiencies From Water Lock-In

	Baseline	Alternative Model Structures	
		Same Entry	No Agglomeration
	(1)	(2)	(3)
Panel A. In Transition (1850)			
Incumbent firm surplus	0.47	0.54	0.39
Entrant firm surplus	0	0.12	0
Consumer surplus	11.38	1.92	-0.08
Capital expenditure	-1	-1	-1
Total	10.85	1.58	-0.68
Panel B. In Steady State			
Incumbent firm surplus	0.74	1.01	0.53
Entrant firm surplus	0	0.20	0
Consumer surplus	22.35	0.85	-0.01
Capital expenditure	-1	-1	-1
Total	22.09	1.06	-0.48

Notes: This table reports effects of reducing firms' switching costs from water to steam power, by paying 1% of total mill output to purchase old water infrastructure. All values are present-discounted and expressed as a percentage of annual output in the initial year. The purchase price is set so that expenditure is always equal to 1% of baseline output. Column 1 evaluates this reduction in switching costs in the baseline model. Column 2 considers effects in a version of the baseline model in which the number of entrants is fixed at its baseline (no-subsidy) levels. Column 3 considers an alternative model without agglomeration in steam power ($\alpha_S = \kappa = 0$). Panel A evaluates a reduction in switching costs in 1850, along the transition path. Panel B evaluates a reduction in switching costs in the terminal steady state. "Incumbent firm surplus" denotes producer surplus, measured by the impact on firm values in the enactment year. "Entrant firm surplus" denotes the surplus for by entrant firms, which is mechanically 0 in columns 1 and 3. "Consumer surplus" is measured as the equivalent-variation effect on consumer prices (see Appendix D.4.2.2 for details). "Capital expenditure" refers to the direct fiscal cost of the switching subsidies, which is mechanically -1 for comparison across scenarios.

Online Appendices

Gaining Steam: Technology Diffusion with Recurring Lock-in

Richard Hornbeck
University of Chicago

Shanon Hsuan-Ming Hsu
University of Chicago

Anders Humlum
University of Chicago

Martin Rotemberg
New York University

September 2025

A Data Construction Details

A.1 Establishment-Level Data from the Census of Manufactures

We collected and digitized all known establishment-level manuscripts from the Census of Manufactures for 1850, 1860, 1870, and 1880 (see Appendix Figure A.1 for example images and Appendix Table A.2 for geographic coverage). This Appendix discusses in detail our collection and processing of these data, their geographic coverage, and how we group counties into time-consistent geographic units.

We located the manuscripts in a variety of state, non-profit, and university archives, as well as some provided by Jeremy Atack which are now at the University of Chicago Library. Most manuscripts were already microfilmed, and the rest we photographed or acquired photos of from archive staff. Our data include some manuscripts that had not been found during the construction of previously-digitized samples described in Atack and Bateman (1999), including Rhode Island and Nevada.

The Census of Manufactures was professionalized and comprehensive beginning in 1850 (Atack and Bateman, 1999). Before 1880, Census enumeration was done in person by US Marshals and all establishments received the same questionnaire, though it changed slightly over time. In 1880, the Census of Manufactures was split into three broad parts: (1) a "general" schedule; (2) a "special agent" schedule; and (3) a "special" schedule. First, many industries received a "general" schedule, similar to that used in 1850, 1860, and 1870. Second, some important sectors were instead given "special agent" schedules, which involved sector-specific questions and specially trained enumerators. These "special agent" manuscripts for 1880 are all believed to be lost (Delle Donne, 1973), which include most manufactures of: cotton, wool, and worsted goods; silk and silk goods; iron and steel; the coke industry; the glass industry; the mining of metals, coal, and petroleum; distilleries and breweries; shipbuilding; and fisheries.[17] Some establishments in these industries were surveyed in the "general" schedule (Atack, Bateman and Margo, 2004).

A third category of sectors were enumerated in "special schedules" with sector-specific questions in 1880, but these were administered by the regular enumerators and these manuscripts were not lost along with the "special agent" schedules. For 1880, these special schedules include "Lumber and Saw Mills" and "Flouring and Grist Mills," along with: agricultural implements; paper mills; boots and shoes; leather; brick and tile; cheese and butter; and slaughtering and meat packing. For example, the additional sector-specific questions include the extent of custom milling for flour mills; and whether a lumber mill does its own logging.

[17] In 1880, cities with over 8,000 inhabitants were surveyed separately from their counties, also by special agents. We found these city manuscripts and they are included in our data.

A.1.1 Variable Coverage

The 1860 Census instructions to enumerators discuss the data collection guidelines in useful detail. In addition to establishment count, our main variables of interest are:

Manufacturing Revenue. Products were valued at the factory gate, excluding transportation costs to customers: "In stating the value of the products, the value of the articles *at the place of manufacture* is to be given, exclusive of the cost of transportation to any market" (emphasis original, United States Census Office 1860*a*). We consider a mill active if it reports positive revenue, and include only active mills in our analysis.

From 1850 to 1870, establishments were asked about the quantities and values for each product, but both units and types were not consistently recorded. For example, flour and grist mills reported quantities in bushels, barrels, pounds, and other units. We attempted to concord across these various units, but without success—partially because in addition to recording different measures, enumerators also used (but often did not record) different units, for instance pounds versus thousands of pounds. As a result, despite extensive efforts, we were unable to measure unit values for 1850, 1860, or 1870.

In contrast, the 1880 special schedules largely avoided these problems by using a consistent unit of measurement for each common product within an industry (e.g., "number of thousands of feet of lumber"). However, the values of products were not reported individually, which means prices can only be computed for establishments producing a single product. There were 2,616 mills producing only lumber, and 296 mills producing only corn meal. Other single-product lumber or flour mills were rare (138 total across all of the 11 products that were also explicitly enumerated). For these 2,912 mills, we calculate average prices by dividing the total value sold by the quantity produced of their sole product.

Input Expenditure. To estimate the demand elasticity ϵ, we need a measure of variable input expenditure. We calculate variable input expenditure as the sum of reported labor costs and materials.[18]

While we cannot directly observe the demand elasticity, we can use the structure of the model to back it out. The optimal price for each establishment is

$$p_{ct}(R,\varphi) = \frac{\epsilon}{\epsilon-1}\frac{w}{\exp(\varphi+\gamma_R+\alpha_R s_{ct})}, \tag{7}$$

$$y_{ct}(R,\varphi) = {P_{ct}}^{\epsilon-\eta}\left(\frac{\epsilon}{\epsilon-1}\frac{w}{\exp(\varphi+\gamma+\alpha_R s_{ct})}\right)^{1-\epsilon}. \tag{8}$$

[18] Total wages paid are reported directly in 1870 and 1880. In 1850 and 1860, we calculate labor costs as the sum (for men and women) of the monthly wage bill times twelve. Materials expenditures are reported directly in the data.

Equation (8) shows that prices are a multiple $\frac{\epsilon}{\epsilon-1}$ of marginal costs, so $\epsilon = \frac{\frac{y_{jct}}{x_{jct}}}{\frac{y_{jct}}{x_{jct}}-1}$. We find that for the median mill, revenues are around 20% higher than expenditures,[19] which implies $\epsilon = 6$.

For the custom milling of flour, millers were paid in wheat, keeping a fraction of what their customers brought. The "millers toll" (the price that could be charged for custom flour milling) was regulated, ranging across regions from a quarter to a sixteenth. The markup for wheat sold on the market was higher (Dondlinger, 1919). Consistent with these regulations, we estimate lower markups in flour (10%) than lumber (33%).

Power Source. The Census also asked all establishments for their number of horsepower used in 1870 and 1880. The kind of power source was asked in every year. Across manufacturing, the most common responses were variations on "steam," "water," "horse," and "hand," which we processed to make those broad categories (as well as "other" and "nothing"). Wind power was relatively rare, and by the time of our sample most American enterprises using tides for power had closed (Charlier and Menanteau, 1997).

In milling, "steam" and "water" were by far the most common power sources. For our main analysis, we exclude mills who report other categories, mostly because there are very few and therefore are difficult to model quantitatively, but also due to concerns about measurement error for the larger ones. We found historical records indicating steam or water power use for several suspiciously-large self-reported "non-mechanized" mills. Since we cannot systematically correct these non-mechanized mills' recorded power-use, we drop them from the main analysis.[20] The one exception is that some mills use "steam" or "water" in their industry name (e.g., "steam mill"), but do not also directly report steam or water as their power source, and for those mills we assume they used the named power source. We do use the reported capital stock of "hand" and "manual" mills to estimate the share of the capital for water powered mills that was due to water power (as opposed to other milling equipment or structures).

Industry. In all years, the general schedule Census asked establishments to report the type of business that they were in. Before 1880, the general schedule Census also asked for the types of products they made. In 1880, most flour mills and lumber mills were surveyed on their own special schedules. Two percent of the flour and lumber mills in 1880 were recorded in the general schedule, and we also include those mills in our analysis unless the same mill was already also recorded in the special schedule.

[19]For estimating the demand elasticity, we only include mills that report all inputs (94% of the sample).

[20]When mills report "horse" as a power source, without further detail, it may often represent water or steam power rather than horse-powered mills. There are few of these mills, though, and our results are not sensitive to including them as non-steam powered mills.

We classify each establishment into one of 31 industries, following Hornbeck and Rotemberg (2024), using information on self-reported "name of business" and products the establishment produced. We describe this process in more detail below.

The Census of Manufactures included some establishments outside of manufacturing, including mining and fisheries. We do not include those establishments in our analysis. In Appendix Figure A.2, we compare totals from our sample of only manufacturing establishments to the published totals compiled by the Census. If the Census included non-manufacturing establishments in their totals (which we can observe that they did in 1850 and 1860), then that might lead to differences. On the whole, non-manufacturing made up less than 2% of the establishments in the data.

Location. The manuscripts record county and state in each decade, based on contemporaneous county names and boundaries. In addition, the name of the closest post office is available for 90% of establishments in 1860, 1870, and the 1880 general schedule. Post office is rarely recorded on the 1850 manuscripts and 1880 special schedules.

A.1.2 Geographic Coverage

Not all manuscripts have survived, which we can assess using contemporaneously published Census tabulations at the county level for 1850–1880 (Haines, 2010) and county-by-industry level for 1860–1880 (Hornbeck and Rotemberg, 2024). Manuscripts for some entire states and decades were lost when the original manuscripts were returned to states. Manuscripts for some counties were lost for reasons such as being used as wrapping paper when returning other manuscripts (Atack and Bateman, 1999). To separate "missing" from "zero," we classify a county as having missing data if the county has no manuscripts but the tabulations report positive establishments; otherwise, we record the county as truly having no manufacturing activity.

For counties with surviving manuscripts, Appendix Figure A.2 shows that our microdata generally align closely with the tabulated county-level data. However, we provide the first comprehensive information on lumber and flour mills in the period because the Census did not report county-industry statistics in 1870 and 1880 for small "local industries" (Appendix Figure A.3, Panel A). For county-industry cells above the Census tabulation threshold, our data align closely (Panel B).

A.1.3 Digitization and Processing of the Census Manuscripts

We worked with Digital Divide Data to double-enter and reconcile data from the manuscript images. In total, there were 65,211 manuscript images with manufacturing establishments, including 28,506 pages from 1880. The average page had 7 establishments. Appendix Table A.2 shows the coverage for which states and decades we were able to find and digitize. When we have records for a state and decade, the records are normally complete for the entire state. In some states and decades, some entire counties or parts of counties appear to be missing when comparing our establishment totals to the published county-level tabulations.[21] We track each establishment's decade, state, county, page, and row.

To help clean the data, we received assistance from many UChicago undergraduates, graduate students, and full-time research professionals. The team checked many entries, finding a low error rate. We used a useful feature of the manuscripts to verify numeric entries: many 19th-century enumerators entered *totals*, such as the total production value for the entire page or for a given firm. We digitized these row totals and page totals, and compared the entered total with the sum of the relevant responses. Consistent with our general data verification, the most common discrepancies arose from totals that were either miscalculated by the enumerators or based on values that were later crossed out and replaced. In these cases, we made no changes. We also manually checked entries with unusually high or low ratios, such as output per worker, drawing on data cleaning processes used by current U.S. Census (Fellegi and Holt, 1976; Thompson and Sigman, 1999; Kim, Rotemberg and White, 2021). We manually changed any cells where we found a difference between entered values and the manuscripts themselves, but did not otherwise "correct" the original written entries.

We manually processed the entered strings for product names, material inputs, and self-reported industry, along with categorizing the entered power strings based on relevant information such as "water" and "steam." The overall goal was to standardize misspellings and British spellings, expand abbreviations, and assign strings to broader categories. To clean industries, we also used the product strings.

The data include many self-reported industry names in each decade, which we group for analysis. Following Hornbeck and Rotemberg (2024), we homogenized industry names into 31 categories, using additional information on products when needed. Our analysis focuses on flour and lumber milling, which were relatively straightforward to classify due to their distinctive outputs. The original manuscripts include over 4,000 distinct industry strings that we associate with flour or lumber milling, including: "grist," "flower mill," "wood & lumber," "steam saw mill," and "mill" (for which product information was needed to identify the industry).

In Appendix Figure A.3, we compare total lumber and flour milling from the estab-

[21] There are 8 counties that, in the manuscripts and tabulated data, have more than 10 firms in an initial decade, no firms in the subsequent decade, and again more than 10 firms thereafter. We drop these counties, as they may be due to enumeration error or missing manuscripts. This approach follows Allcott, Collard-Wexler and O'Connell (2016), who similarly drop firms with observations in a given year that deviate substantially from adjacent years.

lishment data to contemporaneous tabulations, described and digitized by Hornbeck and Rotemberg (2024). Note that although the tabulation data is useful for detecting missing data, it should not be considered as the ground truth. Some counties may have manuscripts that were not tabulated in the census reports or were mistabulated, for instance because of difficulties defining the industry for each establishment.

Some values for string variables were entered in the "wrong place" when the surveyor ran out of space, which we manually corrected. We also corrected cases where numeric variables were mistakenly entered in a string column. Some entries were marked with a question mark by the data processing team when they could not read part or all of a cell. In most cases, we were also unable to read them.

The Census recorded an enterprise as one establishment even if it contained multiple locations within the same Census subdivision, so long as these activities across sites were for the "same concern, and all engaged in the same manufacture" (United States Census Office, 1860*a*). There were also some entries in the Census that were associated with one owner but represent multiple industries (for instance, below we discuss the case of E. E. Locke & Co, which operated a distillery and a mill). We split each establishment into multiple industries, so as to consider only the output of each industry. For instance, when we consider the revenue of E. E. Locke & Co, we only consider the revenue of the mill and not that of the distillery. This is particularly relevant for the mills in the period that produced both cut lumber and flour, which we classify as separate mills in our analysis. This approach follows historical Census practice for multi-industry establishments, which involved "[separating] the two parts of the business and [assigning] each to its appropriate place in the Statistics of Industries" (United States Census Office, 1870*b*). We often refer to "firms" for convenience, though note that the Census enumeration is at the establishment level (unless there were multiple buildings within the same enumeration area) and activity is recorded where it takes place, not at headquarters, so we are then referring to single-establishment "firms."

A.1.4 Adjustment for County Border Changes

Some county borders change over our sample period, and we group together counties with overlapping geographies to create time-consistent borders. This approach is preferable for our analysis of individual mills and establishment-level panel-linking. This differs from an alternative approach of splitting aggregate county activity based on geographic area and aggregating to baseline county borders (Hornbeck, 2010), which would make it difficult to interpret split shares of individual establishments in establishment-level data.

Our baseline county boundaries start with 1850 borders. Issues arise when county polygons from 1860, 1870, or 1880 overlap with multiple 1850 county borders. We group together

1850 counties so that every county from 1860 to 1880 corresponds to a unique grouped 1850 cell.

The first step is to group together all of the 1850 counties that overlap with at least 5% of the area of the same 1860, 1870, or 1880 county.

The second step is then grouping together all of the 1850 counties that were linked in the previous step. As an example, suppose 1860 county a overlaps with 1850 counties i and j, and 1870 county b overlaps with 1850 counties j and k. In the first step, we would group i with j and j with k. In the second step, we create a time-consistent boundary that covers i, j, and k.

We use conservatively large county groupings because we do not want to split individual establishments across counties, which could prevent us from finding the same establishments in subsequent decades. We dropped two grouped counties that have an area larger than a circle with a radius of 50 miles, as this is plausibly too large to be considered a single market. We focus our analysis on counties east of the 98th meridian, where county borders are more stable and settlement patterns are less irregular. Our baseline sample covers 749 counties using the actual 1850 borders, which we group into 689 consistent geographies. For simplicity, we call these consistent grouped geographies "counties" in the text. This covers 83,773 flour and lumber mills, and around 90% of all steam-generated sales in those industries.

A.2 Establishment Panel Linking

This Appendix section describes our creation of a linked panel of manufacturing establishments over time. The Census manuscripts do not have a time-consistent identifier for each establishment, just as in the Censuses of Population (Ferrie, 1996; Feigenbaum, 2015; Ruggles, Fitch and Roberts, 2018; Bailey et al., 2020; Abramitzky et al., 2021; Price et al., 2021), so we generate our own links.

We define a stable manufacturing establishment based on its owner name, industry, and place. If an owner shuts down an establishment and reopens an establishment in a different county, we consider that a new establishment.[22] Similarly, if the owner changes their establishment to no longer be a mill, we consider the mill closed.[23] While we link establishments with partial ownership changes (such as a son taking over from his father), if the establishment's ownership changes entirely, with no clear link between previous and new owners, then we also consider that a new establishment. This is dictated by data availability, and

[22]These cross-county "migrations" appear unusual for millers, based on historical society records (Appendix B.2).

[23]When we hand-linked the establishments, we allowed for cross-industry links and found very few outside of milling. Around 4% of surviving mills switched between lumber and flour.

also raises philosophical questions about what is a surviving establishment. Our view is that mill owners at the time were sufficiently involved in the operation of the establishment that entire ownership changes are akin to closing operations and selling capital assets to a new venture.[24]

We hand-link establishments over time, within a county, using data on owner or company names, industry, product types, and (when available) nearest post office. Importantly, we do not use mills' type of power to make the panel identifiers. We hand-linked all lumber and flour mills, across each decade. Two people searched for matches for each mill, and we reconciled any disagreements. We also trained a machine-learning ("ML") algorithm to predict the matches, described in detail below, which allows us to analyze robustness to different confidence thresholds, and show that the distribution of predicted ML link probability for our actual matches is similar in counties with above and below median waterpower potential counties.

A.2.1 Panel-Linking Procedure

We link mills by hand, from one decade to the next, in combination with a machine-learning linkage model. We employed a team of data associates to compare a mill in one decade to plausible matches in the subsequent decade. We matched mills on name and location, but did not force establishments to be in the same industry in every decade. Because mills rarely switched between lumber and flour, and we consider working in a different manufacturing sector to be part of the outside option in our model, we consider industry switches to be "exits."

To guide the large-scale hand-links, we first matched a few counties and compared every mill to every manufacturing establishment in the subsequent decade. We then trained a machine learning algorithm on those matches. For the large-scale hand-linking, we then only considered potential matches with a relatively high linking probability. For the possible matches, we included candidates with over a 9% linking probability. For mills with many potential links, we only sent the top twenty; for mills with few potential links, we sent the top five as long as their linking probabilities were above 5%. In practice, the potential links with a low match probability were rarely hand-chosen as an actual match. For the analysis in the paper, we then retrained the machine-learning model on the full set of matches. Below, we describe our approach in more detail.

[24] We do find evidence of ownership transfers in historical accounts, though most business closures appear to be associated with the mill no longer being operated. We discuss elsewhere the implications of unobserved reselling, and we use the quantitative model to estimate how local technology choices affect the relative purchase prices of steam and water power, which captures if the transition to steam power lowered the purchase price of water power.

A.2.1.1 Hand-Linking Procedure Our first step was to create some panel links by hand, linking establishments in 1860 to their 1870 counterparts in 97 counties. We chose relatively small counties, to start, so it was feasible to compare all possible matches in the same county: matching 2,709 establishments in 1860 to 5,518 candidate establishments in 1870.

To make the links, we considered each establishment's name, industry classification (including the self-reported string and our own cleaned industry measures), and the nearest post office. We also had access to the original CMF manuscript images for each establishment to double-check mistakes, either in the original handwriting or its transcription. Each hand-linking sheet was completed by two UChicago students, and assigned to a third person to reconcile any discrepancies. For each 1860 establishment, we sorted all 1870 candidates by Jaro-Winkler (JW) name similarity, and by whether or not their broad industries matched, to increase the likelihood that links were at the top of each block of names.

Broadly, we made two types of matches in the data. "Direct" matches are when the establishment names in both periods are close matches. This is similar to common practice in literature linking men across decades in the Census of Population (Ferrie, 1996; Feigenbaum, 2015; Ruggles, Fitch and Roberts, 2018; Bailey et al., 2020; Abramitzky et al., 2021a,b). However, an important difference between linking men and linking establishments is that many mills *actually* changed their names, especially when adding owners. While additional data would be needed to link women who change their last names, our Census of Manufactures data can tolerate moderate changes in ownership. For instance, Appendix Figure A.1 shows the manuscript images for a mill that was initially owned by Alson Rogers, which later passed to his son Lucian. To account for "ownership transfers," we also match establishments where part of the name is very similar but another part is different in a manner consistent with a partial change in ownership. In practice, this second category includes partnership formation or newer members taking on the family business.[25]

A.2.1.2 Model Specification From hand-linking establishments, we noticed there were broadly four categories for how the establishment's name was reported (consistent with guidance from Jeremy Atack). These were not formal rules, but we list the categories below along with our interpretation of their meaning.

1. Establishments with sole proprietorship contain a single owner's name. Names were sometimes initialized, and the names did not consistently follow a first/last name order.

2. Establishments owned by families normally appeared as a person's name followed by *&*

[25]In our replication files, we denote direct matches as "y", ownership transfer matches as "o", and non-matches as "n". We denote direct matches where the industry changed within milling as "s".

sons or *& brothers.* Others appeared with two first names separated by an ampersand, followed by a last name.

3. Establishment that were a partnership or expanded partnership reported two or more names of the proprietors; limited partnerships reported one or more people's names followed by *& co.*

4. Establishments that reported names that were impersonal, and often included tokens related to the business and location.

For our mills, in particular, there were two broad types of naming patterns: those with general company names, sometimes including the name of the water power source; and those named after people. Across Census decades, the order of people's names can change. Even for establishments with a single owner, the order of first and last names can change, along with changes in the use of initials.

These features motivate us to build two separate linking models: one matching the whole establishment name, and one matching owners' names with flexibility in their ordering.[26] We use two random forest models to predict establishment pairs, either tracking the company as a whole or tracking individual owners.[27] Both linking models predict establishment pairs to be: a same-owner match, an ownership transfer match, or not a match. We describe this approach in more detail below.

Name Classifier. We built a name classifier to categorize establishments by their naming pattern type, extract the name of the owners, and identify the name order. While owner names are embedded in establishments owned by sole proprietors, families, partners, or expanded partnerships, the names were often initialized and would switch first-last name orders.

We first use a list of company tokens to identify establishments with impersonal names, which includes: names of locations, such as state and county names; and tokens related to their product or business, such as tanning, manufacturing, lumber, etc.

For establishments without those company tokens, we implement the following steps to extract and format the owner names. First, we remove the non-name tokens, such as "& co" or "& sons," and split the establishment names into owners' names. For a family-owned

[26]We are grateful to Jeremy Atack for suggesting this approach.

[27]We generated linking models based on several classifier families, including logistic regression, random forests, and extreme gradient boosting (Chen and Guestrin, 2016). After evaluating their performance on the validation data, we settled on a random forest trained using the R library `ranger`. The random forest model provided the most reliable output, with respect to false positive and negative rates, and the empirical distribution of predicted probability does not concentrate on the two ends which leaves room for setting the probability threshold and varying the false positive and false negative errors.

establishment with two first names and one last name, we assign the last name to both owners (e.g., turn "J & D. Taflinger" into "J Taflinger" and "D. Taflinger.") We then standardize common nicknames and abbreviations to their original names (e.g., Wm to William and Geo to George.) We determine the name order using the first and last name frequency in the 1880 Census of Population. When both names can be first or last names, we keep both orders and look for both of them in the next Census decade.

Owner Linking Model. Our owner-linking model predicts links based on three sets of information: establishment name, industry, and post office. We define several sets of variables for each of the first, middle, and last names: Jaro-Winkler string distance, whether the name is initialized, and whether the initial matches exactly. When there are missing values, which are incompatible with the random forest model, we assign the median value and define an indicator flag for missing. For industry, we use our industry classification based on the raw industry string to create matching indicators for broad and detailed industries. We also create a measure of industry distance based on the industry classification and similarity in their reported kinds of products. For post office, we use the Jaro-Winkler string distance between post office names and an indicator for missing values.

For establishments with multiple owners, the model predicts matches at the establishment-owner level. At the predicting stage, we take the maximum of the predicted probability for each establishment pair (from all owner pairs) to let the output be at the establishment-pair level. This process allows a firm to match when one owner is the same, even if other owners are different, which mimics how humans generally make links.

Company Linking Model The company-linking model also predicts links based on establishment name, industry, and post office. However, instead of extracting the owner information from the establishment names, this model uses the full string of establishment names and looks for establishments with similar whole names. We use the Jaro-Winkler string distance for the full names, in addition to string distance after removing business and location tokens and the minimum string distance between those remaining tokens among all token pairs. The remaining name distances measure the name similarity unrelated to the business itself, which removes false matches that only have closer string distances on the full name because of common tokens (e.g., "Eagle Mill" and "James Mill").

A.2.1.3 Model Prediction Reconciliation and Hand-Linking We use both models to predict matches, separately, and then take the maximum of the predicted probabilities. For the set of potential matches that we consider when making hand-links, we select the top 20 pairs with a linking probability above 9%. If there are 5 or fewer pairs to send, we send the top 5 pairs with a linking probability above 5%.

We worked with Digital Divide Data (DDD) in Kenya to hand-link the matches, at scale. Our team helped train the DDD associates in person, who also had experience linking individuals across decades in the Census of Population. We then continued to work closely with them remotely, handling the data process ourselves while their managers handled HR.

We sent DDD lists of all potential matches with identifying information: establishment name, industry, post office, and product kinds produced. We did not include the estimated linking probabilities. Two separate members of the DDD team found the best match for each establishment, or indicated no close match, and a third random member reconciled any disagreements between the original two members.

We then iterated on these hand-links using the machine-learning model, asking them to manually check "unlikely" matches or "likely" non-matches. We used the same protocol as for the original data, sending DDD the information about the firm but not the estimated link probability. First, we flagged the following three sets of potential matches for review: (1) links that were made for which the algorithm predicted link probability was below 40%, (2) mills with no links, but for which the algorithm predicted at least one link probability above 40%, and (3) if DDD and the highest-predicted link were different (and the predicted link probability of the actual match was at least 0.1 lower than the best predicted match). For all mills that met one of these three criteria, we resent all of the candidate matches back to DDD for hand-linking. After iteration, the "unlikely" hand-linked matches were generally found to be reasonable matches (and missed by the machine-learning model) and the predicted "likely" matches were also generally decided to be matches after a second look. The automated linking model performed relatively worse in identifying ownership transfers, compared to the hand-links (Appendix Figure A.4, Panel A).

Using this final hand-linked data, after iteration with the original model, we re-estimate the model to create final model-predicted links for our analysis. We consider two mills linked in the baseline ML linking specification if the predicted match probability is above 0.6. To eliminate a small number of multiple links from handlinking (3% of all links), we keep the most likely period 2 link for every period 1 establishment and then keep the most likely period 1 link for every period 2 establishment. There are a few tied matches (0.7% of all links), in cases where adjacent establishments in the same industry have the same owners; in these cases, we randomly select one of the establishments.

A.3 Measurement and Validation of Waterpower Potential

This Appendix section describes in detail how we measure waterpower potential and associated validation exercises.

A.3.1 NHDPlusV2 Data

For each river segment in the country, we use information from the National Hydrography Dataset Plus (NHDPlusV2). National Hydrography Dataset Plus is a national geospatial surface water framework for water resource analysis, developed and maintained by the U.S. EPA in partnership with the U.S. Geological Survey (USGS).

We use NHDPlus Version 2 (NHDPlusV2), released in 2012 (McKay et al., 2012).[28] NHDPlusV2 is built from multiple data sources, including: the medium-resolution (1:100,000) National Hydrography Dataset (NHD), 30 meter National Elevation Dataset (NED), and the National Watershed Boundary Dataset (WBD).

We generate waterpower potential for each "flowline" or "river segment," which is the basic unit in the NHD linear surface-water network. We use the two types of flowlines that represent natural rivers: "Stream Rivers" and "Artificial Paths." A Stream River (SR) is a river segment, often extending between tributary confluences. An Artificial Path (AP) represents a flow-path through a waterbody in the surface water network: for particularly wide rivers, normally those wider than 50 feet and longer than 2640 feet, an "artificial path" is drawn to represent the flow-path within the waterbody.

A.3.2 Theoretical Water Power

For each river segment r, the theoretical water power generated from the flow of water along this segment can be derived using the following formula (assuming no friction):

$$\text{Theoretical Water Power}_r = \underbrace{\text{FlowRate}_r}_{\substack{\text{Cubic Feet}\\ \text{Per Second}}} \times \underbrace{\text{FallHeight}_r}_{\text{Feet}} \times \substack{\text{Gravitational}\\ \text{Constant}}, \tag{9}$$

where the gravitational constant roughly equals 0.1134 when the theoretical water-power is measured in imperial horsepower. This formula closely approximates horsepower calculations in the 1880 Water Census.

Intuitively, the theoretical water power available is proportional to the flow rate of water (volume per second) and its falling height.

Flow Rate. Because there are no detailed or comprehensive measurements of historical water flow, and modern river flows may be influenced by dams and other infrastructure, we use monthly flow estimates from a USGS flow-balance model designed to reflect natural conditions. These estimates are based primarily on natural and slowly changing climatic vari-

[28] Another version is NHDPlus High Resolution (NHDPlus HR), which is at a higher resolution (1:24,000-scale or better) (Moore et al., 2019), but does not currently include monthly streamflow estimates. The resolution of NHDPlusV2 is sufficient for us, particularly given that we later aggregate data to the county level.

ables, such as rainfall, evaporation, and soil moisture, making them suited for approximating 19th-century flow patterns.

Our flow data from NHDPlusV2 are based on the Enhanced Unit Runoff Method (EROM), a five-step procedure for estimating mean monthly flow rates of rivers under natural conditions:

Step 1. Unit runoff based on a flow-balance model, taking into account: precipitation, potential evapotranspiration, evapotranspiration, and soil moisture.

Step 2. Adjustment for excessive evapotranspiration.

Step 3. Adjustment in a log-log regression estimated using reference gauge.

Step 4. Adjustment for flow transfers, withdrawals, and augmentations.

Step 5. Gage-adjustment based on actual observed flow at the gauge.

Step 4 is important for our purposes because the model predicts waterpower potential in the absence of the hydrological infrastructure built in the United States since the 19th century. The modeled water volume reflects natural waterflows that are close to those observed in the 19th century (see below).

Fall Height. For measuring fall heights, we use the difference in elevation between the maximum and minimum elevation along each river segment.

A.3.3 Aggregating to County Waterpower Potential

Appendix Figure A.5 shows flow rates and fall heights for each river segment across the US, whose interactions determine waterpower potential.

For flowlines that intersect county boundaries, we split flowlines into multiple segments that are contained entirely within county boundaries. We allocate the total river segment waterpower potential in proportion to the share of its length inside each county. We then aggregate waterpower potential by river segment to the county level, summing across all river segments in a county.

A.3.4 Practical Water Power

As discussed in the 1880 Water Census: "There is a sharp distinction to be made between *theoretical* and *actually available* water power" (emphasis original). Some sources of water power were infeasible (e.g., the Mississippi River). Below, we discuss several reasons why theoretical water power was not usable in practice and how this enters into our calculations.

River Width. We exclude wide rivers, such as the lower Mississippi River, that were impractical to dam for the purposes of generating water power.[29] These rivers were also used for water transportation, which crowded out water power for manufacturing because millers had to provide rights of way. We use the maximum "top" (surface) width of rivers for NHD segments from the National Water Model (NWM), developed by NOAA (2016).[30]

To explore the influence of maximum river width, we calculate county waterpower potential excluding rivers with maximum widths above different cutoffs. Appendix Figure A.6 plots the coefficient on Lower Waterpower against each chosen cutoff, where the outcome is the number of water mills in 1850 (as in Table 3). There is a sharp attenuation in the relationship for very wide rivers. Our main measure of county waterpower potential therefore excludes rivers that are wider than the 96th percentile (106.3 feet). This cutoff mostly excludes "Artificial Paths" in the database, including most of the lower Mississippi River network, which were impractical for water power use. We also exclude Niagara Falls from our analysis, as water-wheels during our sample period were "inadequate" for the magnitude of the falls (Adams, 1927): there was only one nearby water-mill in our sample, that opened in the late 1870s.

Seasonality and Size. The seasonality of water flow rates is important for the practical use of water power, in addition to average flow rates, because it determines whether watermills can be active throughout the year. Some mills were more seasonal, using water power when available, but the strong tendency was for mills to focus on year-round water power availability.

For many rivers, water flow rates varied over the year. We use the average flow rate over the three lowest months of the year, as historical accounts viewed this as a key determinant of feasible water power (United States Census Office, 1883). Consistent with these accounts, while we include "intermittent" rivers in our analysis, they do not on their own predict water power-use (Appendix Table A.3, Column 2). Similarly, the average flow rates across all 12 months are less predictive of county water power-use in 1850 than our baseline approach (Appendix Table A.3, Column 3).

For our main analysis, we use the average waterpower potential per unit area in the county. But because waterwheels are fixed in a single location, a site with 10 horsepower would have been more useful than 100 sites with 0.10 horsepower each. Appendix Table A.3, Columns 4, shows that our results are similar if we only include segments with economi-

[29]For example, the 1880 Water Census writes: "...the Mississippi as it flows past New Orleans gives an exhibition of tremendous force, and by damming it up to a head of 10 feet a power of nearly 700,000 horse-power would result, but the river would be flooded back for 300 miles, and the plan is therefore impracticable."

[30]For more details of the National Water Model, see `https://water.noaa.gov/about/nwm`.

cally meaningful waterpower potential—those with more than 2.75 horsepower per mile, the smallest site highlighted by the 1880 Census "Reports on the Water Power of the United States" (the "Water Census").

A.3.5 Validation Exercises

We validate our use of NHDPlusV2 data on waterflow using historical records from the Water Census. Consistent with the historical importance of water power, the US government spent resources to promote its use even in 1880: the stated purpose of the Water Census was to "describe the privileges actually in use and call attention to locations where power could be advantageously developed." For river segments covered in the historical Water Census, their flow rates are in close agreement with the modern data (Appendix Figure A.7).[31]

We do not directly use the Water Census to measure county waterpower potential because its coverage is non-random and incomplete, as it was based on historical economic activity (Appendix Figure A.8, Panel A). The Water Census was intended to focus on places with high waterpower potential or usage, systematically missing places with lower waterpower potential and lower usage. Further, the Water Census effort ran out of funds before reaching much of our sample area (Atack, Bateman and Weiss, 1980).

We would expect estimates based on the 1880 Water Census to be biased toward zero, as the 1880 Water Census effectively selected on the dependent variable (by omitting places with lower waterpower potential *and* lower water power use), which we confirm when looking at the number of water powered mills in 1850 (Appendix Figure A.8, Panel B) or 1850–1880 growth in mills (Panel C). Panels B and C also show that the estimated impacts on mill activity from county waterpower potential are roughly linear, which validates our focus on linear specifications in the analysis.

A.4 Supplementary County-Level Data

This section provides additional detail on some of our supplementary data.

Market Access, Navigable Waterways, and Railroad Stations. We use measures of county "market access" in 1850 (Donaldson and Hornbeck, 2016; Hornbeck and Rotemberg, 2024). Market access is approximated as:

$$MA_c = \sum_{d \neq c} (\tau_{cd})^{-\theta} L_d. \qquad (10)$$

[31] There are some exceptions where the values diverge, which generally reflect segments where merging the two datasets is difficult (e.g., if a river splits into several sections and it is unclear how many segments to aggregate when comparing our smaller river segments to what the Census considered a river segment, or when distinct rivers in a county share a name).

The market access of county c is the trade-cost-weighted sum of population L in other counties d, where the iceberg trade cost τ is raised to the power of the trade elasticity. We set $\theta = 3.05$, following Hornbeck and Rotemberg (2024), and control for the log of county market access in 1850. For some specifications, we also use county market access in other decades.

Measured transportation costs are based on least-cost routes using railroads, navigable waterways, and wagon transportation. We also control directly for whether the county is on a navigable river (as defined by Fogel 1964) or other navigable waterway (canal, lake, or ocean), and log distance to the nearest navigable waterway (based on average distance from 200 random points in the county to the nearest navigable waterway). Using maps of the railroad network in G.W. & C.B. Colton & Co (1882), we also collect detailed locations of railroad stations.

Coal Access. We digitized maps of workable coal deposit locations from Campbell (1908), a survey run by the United States Geological Survey. The map shows workable deposits for each type of coal (lignite, subbituminous, bituminous, and anthracite), and we calculate both if the deposits overlap with a county and the share of the county with a deposit. In addition to using measures of coal in the county, we also calculate the lowest-cost "iceberg" transportation cost from any workable deposit to each county along the transportation network.

Specifically, we assume that if there is coal in a county, there is no transportation cost to access coal. If there is no coal in a county, we calculate (a) the cheapest cost to a county with coal, using the iceberg transportation costs calculated by Hornbeck and Rotemberg (2024). We also calculate (b) the minimum wagon cost (again using the Hornbeck and Rotemberg 2024 costs) from the border of the county to the nearest coalfield. We then calculate the relative cost of shipping as the transportation cost divided by the price of coal, using the minimum of (a) and (b). We follow Cole (1938) and calculate the weighted average price of coal in 1880 (40% anthracite and 60% bituminous), using commodity prices from the Statistical Abstract of the United States (Bureau, 1919). In addition to data on coal deposits, for some specifications we use data on coal mines from the 1850 Census manuscripts: we define an indicator for any active coal mine; the arcsin of production in dollars; and, as above, the cheapest cost to a county with coal production.

Local Milling Material Availability. We measure counties' wheat suitability using historical crop suitability data from the Global Agro-Ecological Zones project of the Food and Agriculture Organization (GAEZ-FAO). The data reflects rainfed conditions, low input use, and no CO_2 fertilization. We also use counties' acreage share in woodland in 1870

(Haines, 2010).

Portage Site Locations. Following Bleakley and Lin (2012), we use data from Semple (1903) and Fenneman (1946) to measure whether counties contain actual or potential portage sites based on the fall line. We also included the historic location of portage sites along the Ohio, Missouri, and Mississippi rivers described by Bleakley and Lin (2012).

The Water Census. We digitized the "detailed tables" of the Water Census, for comparison, which gives us information on waterpower potential at the level of the site, which we then aggregate to the county level as we do with the NHDPlusV2.

B Historical Context

Steam power was not a strictly dominant technology, such that water and steam power were both utilized even into the 20th century (Atack, 1979). In our analysis, we estimate that steam powered mills were larger because they had lower marginal costs of production (and therefore charged lower prices). We further estimate that, over time, the purchase price of steam power declined and, across space, that higher local waterpower potential lowered the purchase price of water power. This section provides more historical and descriptive evidence that not all millers wanted to use steam power because it required higher fixed costs (higher operating costs, in particular, as also emphasized by Atack 1979, and higher purchase prices at the start of our sample).[32] We also show that declining steam purchase prices are consistent with qualitative histories of steam use in rural US milling, which emphasize the development of practical low-cost engines.

B.1 Historical Background on Water and Steam Power in US Mills

Water powered milling has a long history in the United States, as the Massachusetts Bay Colony built several watermills in the 1630s, some of which remained in use into the nineteenth century (Weeden, 1890). Mullin and Kotval (2021) note that Puritans believed every "town required four essential elements if it were to succeed: a meeting house with a pastor, a blacksmith, a sawmill and a grain mill." Flour and lumber mills were needed throughout the country, using the available local water power. They could use smaller rivers and did not typically require large installations. In contrast, textile mills could be agglomerated in major manufacturing centers in places with substantial waterpower capacity. Hunter (1979, 1985) provides an overview of water and steam power in the 19th century,[33] and we summarize a few key features of this context.

Most flour and lumber mills served their "local clientele" (Brown, 1923), though some

[32] We thank Jeremy Atack for providing accompanying notes that illustrate the higher upkeep costs associated with steam power.

[33] See Howes (2023) for a description of innovations in steam power before the 19th century.

"merchant mills" served cities and export markets (Kuhlmann, 1929). The nationalization of these industries occurred after our sample period. Flour milling began to concentrate in Minneapolis in the 1880s, after the development of less-perishable flours made possible by the middlings purifier and the roller mill (Kuhlmann, 1929; Perren, 1990). The rise of the milled lumber trade was facilitated by the emergence of manufacturers' associations to create and maintain standards (such as those regarding sapwood and knots). These associations did not exist in lumber until the 1880s, and did not reach prominence until the 1890s (Brown, 1923; National Industrial Conference Board, 1925).

The fundamental change from the arrival of steam power was a new source of mechanical power, less subject to natural constraints (Hunter, 1985): steam power was not as expensive to scale up, and it offered consistent year-round access to power. As a result, steam power was particularly useful in places with less local waterpower potential (Sharrer, 1982). These places had higher fixed costs for using water power, due to greater need for constructing dams, millponds, and riverwalls, which were generally more expensive to build than the wheels themselves (Monroe, 1825). Places with lower waterpower potential may have also required higher costs for securing water rights.[34] While water power technology improved over the 19th century, for instance with the development of the Jonval turbine in the 1840s and the Pelton wheel in the 1880s (Hunter, 1979), the more-substantial forces were that steam improved substantially over time and that waterpower availability varied substantially over space. For instance, a congressional report discussing options for a national armory on the "Western Waters" (Armistead, Lawson and Long, 1841) used, without updating, the estimated costs of water power from a previous Presidential report (Monroe, 1825).

While steam offered advantages, it was not a strictly dominant technology, as it required high non-variable costs: "the first cost of steam engines, and their annual expense, do not increase or diminish in proportion to the size of each engine" (Monroe, 1825). For instance, steam equipment required installation and continued maintenance oversight from trained engineers (Fisher, 1845).

Early steam engines were not widely adopted in the early United States.[35] With the introduction of the Corliss engine, patented in the US in 1849, manufacturing hubs in the

[34]Swain (1888) reports the cost of water rights for 25 counties, which are negatively (though not significantly) correlated with our measure of waterpower potential.

[35]Early Newcomen engines were coal-intensive and inefficient, wasting energy in the process of heating and cooling water to drive a piston in a cylinder. In the late 18th century, James Watt introduced a separate condensing chamber so the primary cylinder never needed to be substantially cooled, which dramatically improved the efficiency and force of British engine designs.

In the spirit of Arrow (1962), steam engine manufacturing was characterized by learning-by doing, as many subsequent improvements to Watt's design came as machinists gained experience and tinkered with the size and arrangement of the parts.

US were increasingly using more-sophisticated and massive steam power systems. But these increasingly large and intricate systems were not particularly suitable for the small local mills throughout the US.

Local mills focused on relatively cheap "high-pressure" engines, patented and evangelized by Oliver Evans in the early 19th century, which did not use a condenser and instead used substantially higher pressure in the boiler. These engines were smaller and had substantially lower fixed costs, but were prone to explode (Burke, 1966; Mayr, 1975). Over the 19th century, many engineers adapted and improved on the standard designs (Thurston, 1878), which allowed mill owners to purchase steam engines at steadily decreasing prices. Further, as local expertise in steam power spread geographically, increased local construction of steam machinery reduced shipping and installation costs (Greenberg, 1982).

In the second half of the 19th century, US mills began using "high-speed" engines that drew on earlier high-pressure boilers. High-speed engines were smaller and cheaper, though the parts needed to be made precisely to avoid the machine shaking dangerously and exploding.[36] New high-speed engine designs were introduced by Porter and Allen in 1862, and were described contemporaneously as a "revolution in engineering" (Scientific American, 1870). Porter (1868) argued that their design required efforts that machinists "were now thoroughly accustomed to," and that the "commercial benefits" to the engine included "the saving of space and the economy in first cost."

B.2 Switching Case Studies from Historical Society Records

For some cases in which incumbent water mills adopted steam power, we looked through historical society records (and other documents, when possible) for guidance on why these mills adopted steam and what impediments to steam adoption may have confronted incumbent water mills. This qualitative history of switching helps motivate assumptions of our model for why water incumbents faced higher costs of steam power than entrants.[37] The available historical detail was limited in most cases, or we were unable to find records for the mills, though we could generally see that most millers did not change locations and verify Census data on when mills switched to steam power.

Qualitatively, the most common reason why mills switched to steam power we found was they outgrew the power availability of their local waterway, or they lost their local water rights (Emery, 1883), which is consistent with sunk investments in water power creating switching costs. A few millers physically moved their operations to a new structure when

[36] Although steam engines and boilers got safer over time, explosions are often described in histories of individual mills and, during the period, a plurality of steam engine explosions were in lumber mills (Scientific American, 1871, 1881).

[37] We are particularly grateful to David Kirchenbauer and Tony Li for outstanding research assistance in finding these historical sources. We also include examples of switching that we found in secondary sources.

switching power sources, but most retrofitted their existing mills in place even after losing the original motivation for their location. Many switches from water to steam power were associated with a change in ownership, often through sons taking over from their fathers, which suggests switching frictions on the part of operators and points to the importance of management (Bloom et al., 2013; Giorcelli, 2019).

Below, we provide some examples of millers (in alphabetical order) for whom we were able to find more-detailed information. These case studies suggest some of the push and pull factors behind mills switching from water to steam power:[38]

The Blanchards Brick Mill was built in 1842 in Watertown, Wisconsin (Watertown Historical Society, 2022). Due to concerns about low flow from the Rock River, the proprietors started construction of a steam mill (next door to their original mill) in the 1840s, though in our data the mill did not switch to steam until the 1860s.

The Canal Mill in Erie, Pennsylvania was sold by Jehiel Towner to Oliver & Bacon in 1865, who immediately converted it to a steam mill (Bates, 1884). Oliver & Bacon had previously operated a mill called Hopedale, located in the same county but outside the city, but left it to purchase the Canal Mill.

The Ellis Mill was built around 1838 by Moses Ellis, in Fayette County, Indiana (Barrows, 1917). After Moses' death in the 1840s, his son Lewis operated the mill for a few years, until he abandoned the watermill in the 1850s and built a steam mill in nearby Bentonville.

Elhanan Garland owned a water powered mill on the East bank of a stream in Kenduskeag, Maine, and Moses Hodson owned a water powered mill on the West bank of that same stream (Hubbard, 1861). After a lawsuit, it was determined that Garland had the senior water rights for using two stones of grist mill, but Hodson's rights were prior to Garland's for other purposes (such as a saw mill). Garland subsequently switched to steam power, but did not change locations.

Charles Gwinn, who was already a prominent miller exploiting high water power availability in Baltimore, built a steam powered mill there in 1813. He did not use steam power for very long, though, as it became clear that steam was "too costly to operate for milling flour" relative to water, in Baltimore at that time (Scharf, 1874; Sharrer, 1982).

The Graue Mill in Oak Brook, Illinois (which is now a museum, conveniently close to Chicago) was a gristmill that opened in 1852 (York Township Historical Society, 2023). The ground was relatively flat, so the immigrant owner (Frederick Graue) had to construct a dam to create a three foot fall. In order to expand, Graue spent three years retrofitting his mill for steam use (including the help of a visiting millwright). Graue had also made his own bricks on site, for the building, and seemed quite entrepreneurial and adventurous in

[38] We provide an additional example in Appendix Figure A.1.

further modifications prior to the steam engine's explosion.

The Hardesty Brothers inherited a profitable grist mill in Canal Dover, Ohio after their father died in 1869 (Hardesty, 2019). Within a decade, they borrowed money to buy a steam engine (without changing the location of their mill). The mill dissolved a few years later, and Hardesty (2019) speculates that one possible reason was due to the heavy financing needs.

Chauncey B. Knight inherited a water powered flour and grist mill built by his grandfather Nicholas Knight in Monroe, New York (Flour and Feed, 1945). Close to what is now Harriman State Park, the location has excellent access to water power. Knight converted the mill to run on steam power, which was the first steam mill in the county. Knight recounted that "it was freely predicted that it would be a failure," as many thought steam "could not compete with water power which was so much cheaper." Knight's mill was large enough to process corn meal, wheat bran and middlings, and malt sprouts by the "carload," with the bulk discounts allowing his mill to sell meal much more cheaply than his competitors.

E. E. Locke & Co operated a distillery along with a mill in Mifflin, Pennsylvania (Ellis and Hungerford, 1886). The mill only used water power in 1850 and only used steam power in 1860. The distillery and mills of E. E. Locke were destroyed by a fire in 1857. The rebuilding and the restoration was finished by 1858. We suspect that the mill switched from water to steam because of the fire.

David and Andrew Luckenbach purchased a grist mill from their father in 1861 in Bethlehem, Pennsylvania (Jackson, 1975). As the business expanded, "the water power provided by Monocacy Creek was found unsatisfactory," and they installed steam engines in 1877 after a fire destroyed the original mill.

J.S. Manning owned a mill in Columbus, Wisconsin that used only water power in 1870 and used only steam power in 1880 (Jones, 1914). He purchased the mill in 1849, which was already the busiest mill in Central Wisconsin. It is described that the wait for grist work was often weeks. Manning is described as switching to steam power to keep up with demand. When the mill switched from water to steam power, the location of the mill did not change, though new machinery was added to the pre-existing mill.

John Orf purchased a mill in Allen County, Indiana in 1856 (Bates, 1945). Water from the Wabash and Erie Canal was taken into a mill pond just east of the St. Mary's aqueduct and run across an overshot wheel. Anticipating the canal's closure, Orff retrofitted the mill to be able to run on either steam or water power in the 1870s. The canal closed in the 1880s, at which point Orf's mill used steam power exclusively.

The Phoenix Mill in Millwakee, Wiscosin was built by brothers William and Edward Sanderson in 1847 (Andreas, 1881). William died in 1868, and Edward added Isaac van

Schnaick as a partner. They expanded the business, and switched to steam power.

The Shoemaker Mill was built in 1746 on a mill race off Tookany Creek in Montgomery County, Pennsylvania Rothschild (1976). The family operated the mill for 100 years before it was purchased by Charles Bosler, an employee. After Charles died, his son Joseph enlarged the mill and converted to steam power.

Williams & Lufbury owned a water powered lumber mill in Rahway, NJ (International Publishing Co, 1887). The mill used water power in the 1850 Census and steam power in the 1860 Census, without changing location. During that time, dams were abolished within the city limits.

Emery (1883) describes an (unnamed) water mill forced to switch to steam power because it lost its water rights. Emery (1883)'s goal was to describe the cost of switching to steam power, as testimony for a hearing to determine how much the mill should be compensated.

B.3 Additional Descriptive Statistics

While mechanical power eventually spread throughout manufacturing (Atack, Margo and Rhode, 2019, 2022), we focus on two industries that had widely mechanized before steam arrived to study the transition of mechanical power from water to steam. Most water powered establishments in 1850 were either lumber or flour mills (Appendix Figure A.9, Panel A). Flour milling was the largest industrial sector in the economy during our period, by revenue, and lumber milling was the largest by number of establishments. Textile mills were also heavily-mechanized, though records for textiles in 1880 have been almost completely lost.

Among lumber and flour mills in 1850, 91% report using either water or steam power. Around 1% of mills used both water and steam power, which we classify as steam mills because they paid the fixed costs of steam and thereby benefited from the ability to scale relatively cheaply. Non-mechanized mills contributed little revenue share (Appendix Figure A.9, Panel B), and our main analysis omits these non-mechanized mills.

Mills had substantial local competition. The median county-industry had 10 mills operating in a given year. Almost all county-industries had more than one mill (96%). Of these, 62% had at least one mill using each type of power and this share increased over time as steam power became more prevalent.

A useful feature of lumber and flour mills, for our analysis, is they primarily served local demand because cut lumber and ground flour were perishable and not economical to trade to farther destinations (Hunter, 1979). Indeed, an important source of revenue for flour mills was "custom milling": grinding grain that local customers brought themselves (Dondlinger, 1919; Le Bris, Goetzmann and Pouget, 2019). The Census asked specifically about this practice in 1880: 95% of mills did at least some custom milling in 1880, and it represented 41% of total flour milling output. While milling was dependent on local geographic endowments to generate power, the material inputs (logs and whole grains) for these mills were less perishable and could be transported long distances, so the local endowment of inputs was not as important for millers (Cronon, 2009).

Consistent with historical accounts that flour and lumber milling produced relatively non-tradable output, Appendix Figure A.10 shows that the spatial concentration of lumber and flour mills was particularly low (in the spirit of Mian and Sufi 2014).[39] This contrasts with clothing and textile mills, whose output was more easily traded and so was much more concentrated geographically. Lumber milling remains diffused: in the 2021 County Business Patterns, 98% of commuting zones had a lumber mill and 25% had a flour mill.

B.4 Cost Structures

B.4.1 Power Cost Structures and Firm Size Distributions

Each power technology was associated with marginal costs and fixed costs (where fixed costs include both purchase and overhead costs). Because neither technology was clearly more attractive to millers, we model steam power as better on one cost dimension and water power as better on the other cost dimension.

To distinguish which technology has which features, we use a logic in the spirit of Melitz (2003) (see also Olmstead and Rhode 2001; Cabral and Mata 2003, and Bustos 2011). Millers have different productivities, for instance due to their ability to attract customers, manage suppliers, and operate the machinery (Huntington, Samaniego dela Parra and Shenoy, 2023). Holding firm productivity fixed, firms will be larger if they use the lower marginal cost technology. More-productive firms are also more likely to prefer the high fixed cost and low marginal cost technology, because they can amortize the fixed costs over more units. Combined, this means that the technology associated with larger firms is the one with lower effective marginal costs.

Figure 4 shows that steam powered mills were larger than water powered mills, on average, which implies steam power has higher fixed costs and lower marginal costs than water power.

Other features of our data are also consistent with this interpretation of the firm size distributions. Steam users were more likely to exit, despite their higher revenues, which is consistent with higher fixed operating costs that were more difficult to cover (Table 2). Further, while firms do not report the cost of power in the Census, they do report the total value of capital investments and these capital costs are indeed higher for steam users,

[39] The other least geographically concentrated sectors are leather and iron & steel (due to blacksmithing, as discussed by Atack and Margo 2019).

consistent with higher purchase prices. Finally, for products that we can compare across different producers, steam users charge lower prices, consistent with lower marginal costs.

Contemporaneous accounts of US mills discuss the low prices that steam powered mills were able to charge (e.g., Flour and Feed, 1945), due to their low marginal costs of production. Indeed, the first steam powered grist mill, constructed in London in 1781, charged notably lower prices than its competitors due to its "economies of production" (Westworth, 1932). We are only able to study prices for single-product mills in 1880, due to data constraints described in Appendix Section A.1, among whom steam use predicts lower mill output prices in both lumber (by 6%) and flour (by 1%).

The estimated higher fixed costs of steam power, and lower marginal costs, requires some further clarification because steam power does require daily expenditure to access mechanical power in contrast to natural water flow. But many of these costs for steam power were fixed overhead costs, rather than marginal costs, which is in turn reflected in the firm size distribution. Even small steam mills employed full time engineers and firemen and mills used a relatively consistent amount of fuel to keep their engines on throughout the day and avoid ramping costs (Fisher, 1845; Swain, 1888).[40]

Further, the *effective* marginal costs of water power were higher than their *inframarginal* variable costs. Waterwheels were limited by their local geography: the size, speed, and reliability of their local waterway, as well as contractual water rights. Firm behavior reflects not only the monetary expenditure for marginal power use for water mills, but also the shadow costs associated with expansion. Some water powered incumbents did grow (Appendix Figure A.11), so water powered mills were not completely constrained, but expanding production further could require increasingly expensive modifications to their operations. On average, the water incumbents who stuck with waterpower expanded their horsepower capacity by 7% and those who switched to steam power expanded their capacity by over 50%.

Finally, the relevant marginal costs are those of *production*, not of *power* alone. Appendix Figure A.12 shows that steam mills had access to more power than water powered mills, lowering the non-power marginal costs of steam powered mills (for instance, because the mill could process more inputs per hour or use the mechanical power to assist with more tasks (Evans, 1795; Manning, 1889; Dedrick, 1931)).

While we emphasize that the fixed costs of steam power were not just capital costs, we

[40]In their studies of large cotton mills, Temin (1966) and Halsey (1981) discuss the low cost of flowing water in contrast to fuel costs of steam. However, the engineering costs associated with power generation are not the same as the marginal costs of production, which are the relevant costs for millers. Furthermore, the cost structures of the largest mills in the world studied by Temin (1966), located at the most advantageous waterpower sites, may have been different than the mills we study that were geographically dispersed and sold to local consumers.

can measure capital stocks directly in the Census manuscripts. Appendix Table A.4 shows that, on average, steam users had around 20% more capital. Over time, the total physical investments of steam users shrank towards those of water users. We find similar patterns when considering all establishments, or when constraining the sample to entrants.

B.4.2 Declining Fixed Costs of Steam Power over Time

Figure 4 shows that the size distributions for steam and water powered mills converged over time. This suggests a corresponding decline in the fixed cost of steam power, as less-productive firms started to find steam power more attractive. By contrast, a declining marginal cost of steam power would have increased the size premium of steam powered mills. Declining fixed costs of steam power are also consistent with the development of high-speed engines that reduced steam fixed costs for lumber and flour mills.

Figure 4 also shows that the convergence of firm size distributions is partially driven by the left tail of low-productivity water mills disappearing over time. In our model, increasing competition (driven by the spread of steam power) crowded out the least productive water mills. Collard-Wexler and De Loecker (2015) document a similar pattern in US steel manufacturing during the spread of the minimill.

One potential explanation for these observed patterns could be that steam power shifted activity to new locations that, for unrelated reasons, had mills of different sizes. This geographic shift is not driving our results, though: Appendix Figure A.13 shows firm-size distribution patterns we find are similar within-counties (for counties with both types of mills).

B.4.3 Higher Fixed Costs of Water Power in Counties with Lower Waterpower Availability

For higher local waterpower potential to make water power use more attractive to firms (as in Appendix Figure A.8, Panel B), it must have lowered the fixed costs or marginal costs of using water power. If waterpower potential lowered the marginal costs of water power, then counties with higher waterpower potential would have larger water powered mills (and, due to the resulting selection, also larger steam powered mills). Appendix Figure A.14 shows this was not the case and, indeed, somewhat the opposite: in most decades, counties with higher waterpower potential have more small mills. Thus, we model county waterpower potential as lowering the time-invariant fixed costs of water power, such as the costs of water rights and constructing millponds.

Waterpower was associated with capacity constraints, and some millers required power that their local river was unable to provide (Hunter, 1979). As noted by Hsieh and Klenow (2009), capacity constraints enter the optimization problem of producers similarly to marginal costs: producers will charge higher prices to avoid hitting the constraint. Steam power would then attract more-productive millers because it was easier to scale.

Nevertheless, while capacity constraints were relevant for some millers, we find evidence inconsistent with capacity constraints being the primary driver of differences between water and steam powered mills.

First, in our data, counties still had substantial available waterpower capacity. The median county used less than 10% of the available waterpower potential, and over 96% of counties used less than half of the available waterpower potential.[41]

Second, Appendix Table A.5 shows that waterpower potential had roughly similar effects on the exit probabilities of steam and water incumbents. If water incumbents were capacity constrained, but had low marginal costs for their inframarginal production, then they would be less affected by increased competition than the steam incumbents, as constrained incumbents would be relatively able to lower their prices in response to increased entry.

Third, if capacity differences were a primary driver of power choices, this would imply that water incumbents would be *less* likely to switch to steam power in places with lower waterpower potential: the increased competition due to steam entrants would make it less likely that water incumbents would exceed their capacity. By contrast, Table 6, Column 2 shows that water incumbents were *more* likely to switch to steam in locations with lower waterpower potential.

C Supplemental Empirical Results

C.1 Technological Persistence and Switching

A striking empirical pattern motivating our analysis is the limited switching from water power to steam power among incumbents, particularly in contrast to entrants' greater use of steam power. In our analysis, we interpret this inertia as driven by lock-in. This Appendix explores other potential explanations that could contribute to reduced switching by incumbents in our data, explaining why switching barriers are our preferred explanation.

C.1.1 Learning-by-Doing

Across different contexts, one potential explanation for low technology switching by incumbents is learning-by-doing (Jovanovic and Nyarko, 1996). For our context, though, a high rate of learning-by-doing in water power usage is inconsistent with the longstanding use of water power in the United States. By the beginning of our sample period, water power was a commonly used and broadly understood power technology.

[41] Hunter (1979) and Gordon (1983) report that standard estimates of waterwheel efficiency in the era were at least 50–70%.

The logic of learning-by-doing would be that water powered incumbents could have freely adopted steam, but did not want to because they had increasingly learned to use water power and, for them, it continued to dominate steam. Appendix Table A.6 tests three implications of this logic, and does not find evidence for learning-by-doing that might be benefiting water incumbents and discouraging their adoption of steam.

First, Panel A shows that the establishments that maintained their waterpower use grew substantially more slowly than those that switched to steam power (rather than water continuers benefiting from their gained technological experience with water). In our model, we rationalize the relative growth of steam power with both the direct effects of steam power and selection in which enterprises switch.

Second, we leverage a prediction from the learning literature that the young learn more than the old, as they have more scope for discovery (Traiberman, 2019). In our context, this would imply that if learning-by-doing were important, we would observe faster growth for young water continuers rather than older ones. Panel B shows that, instead young and old establishments grow at the same rate.

Finally, in the spirit of Bahk and Gort (1993), if learning-by-doing were important, then all incumbents would tend to grow faster than successive generations of entrants, as the incumbents benefit both from learning and from any other general economic changes that would increase firm size. In Panel C, we compare the growth rate of water incumbents who keep using water power to the growth of entrants, and find that their growth rates were similar.

C.1.2 Productivity Costs from Switching Technologies

We model switching barriers as equivalent to an expenditure (a combination of the opportunity cost of scrapping a functional power source and other actual costs such as retrofitting). An alternative modeling approach could assume a *productivity* cost from switching technologies (see, e.g., Parente and Prescott 1994). For our context, productivity losses are less plausible because most of the day-to-day operations of milling are the same with either power source. Further, switchers grow faster than stayers (Appendix Table A.6), which is not consistent with productivity losses from switching. Indeed, even though water incumbents were initially negatively selected (because only firms with relatively low initial productivity chose water power), those that switched to steam power were 1.87% larger than steam entrants.

C.1.3 Heterogeneity in Firm Types

Another potential reason why incumbents would not switch technologies is permanent unobserved heterogeneity in technology preferences (i.e., "steam types" and "water types"). Historical accounts of mills discuss instances of mills switching technologies after a fire destroyed their original structure (Appendix B.2), which suggests owners do not persistently prefer a particular technology, but instead face sunk fixed costs or other barriers to switching (Hornbeck and Keniston, 2017; Huesler and Strobl, 2023). We can further explore, however, how permanent idiosyncratic variation in costs and productivity might align with the data.

Appendix Table A.6 shows that firms' revenue grew more when they switched, which is not a general prediction of models with persistent types, but is a prediction of a model with switching barriers (as only the mills with productivity growth would choose to change technologies). In particular, one specific concern might be that water entrants were forced to locate in otherwise unattractive locations to have access to waterpower. This would imply that the water-to-steam switchers would be smaller than the steam entrants (who were more flexible in choosing the site of their mill). However, switchers were 2% larger than entrants.[42]

We can also use the timing of mills' water use and steam use to compare the implications of switching barriers versus heterogeneous types in generating the observed state-dependent technology choices. Methods of quantifying the importance of state dependence versus types require observing agents for many periods (Lancaster and Nickell, 1980; Chamberlain, 1985; Dano, 2023), whereas we observe mills for a maximum of four census rounds (and normally fewer). We provide two alternative tests, in the spirit of Chay, Hoynes and Hyslop (1999), which are inconsistent with the presence of types driving relatively low switching rates.

One test of state dependence is to examine firms' technology choices, conditional on their prior use of water and steam power. Consider the sample of mills over four periods who start with water power, end with steam power, and use steam power exactly twice. These mills use steam power half of the time, and all have the same initial and final conditions (as in Hotz and Miller, 1993; Arcidiacono and Miller, 2011). Switching barriers would make it substantially more costly for these firms to alternate between technologies twice, as opposed to using water for two periods and then steam for two periods. By contrast, under heterogeneous types, switching is driven by period-specific idiosyncratic shocks, so each pattern would be equally likely. In our data, the vast majority of these mills switch technologies only once and then keep their new technology, which suggests switching barriers are driving technological choice.

The second test is based on the logic that under persistent heterogeneity, a Bayesian observer would update that a water powered incumbent who previously also used water power would be more likely to be a "water-type" than a water entrant, since the former chose water power multiple times. This would subsequently imply that the water incumbent stayers would be more likely to use water power than water entrants in subsequent decades,

[42] Another potential source of differences in technology use for entrants and incumbents could be differences across locations, if the (new) steam users locate in different places than the (pre-existing) water users. We find significant differences in adoption choices within counties, however, and we compare technology choices within county-industries when estimating the relevant moments in Section IV.D.

but this is not what we find in the data.

C.1.4 Resale of Water Power Infrastructure

We do not observe if entrants build their own mills, or if they purchase used mills, but the resale of water infrastructure would generally attenuate the differences between entrants and incumbents. If persistent county-level infrastructure were important to the choices of entrants, then they too would face opportunity costs of using steam, and they would not be substantially more likely to use steam power than the water incumbents. Nevertheless, Table 6 shows that entrants are particularly more likely to use steam power in places with lower waterpower potential, which have relatively higher exit of waterpowered establishments.

C.2 Robustness of Main Estimates

C.2.1 Robustness to Alternative Controls

Appendix Tables A.7 and A.8 consider other county-level characteristics that could affect relative mill activity and steam adoption across counties with different waterpower potential. The outcomes in these tables are our main county-level outcomes: the number of water mills (Column 1) and the steam share (Column 2) in 1850, the growth in total mills over each decade (Columns 3–5), and the change in the share of mills using steam power (Columns 6–8). In each table, the first row corresponds to our main specification for comparison.

In Appendix Table A.7, we show that our results are robust to including various characteristics that have been discussed as important drivers of steam power adoption across different contexts (Crafts, 1977; Floud and McCloskey, 1981; Allen, 2009; Mokyr, 2016): alternative measures of access to coal (Wrigley, 2010; Fernihough and O'Rourke, 2021; Reichardt, 2024);[43] agricultural productivity and woodland that affect mills' material input availability (Nurkse, 1953);[44] differences in labor availability reflected in manufacturing wages (Habakkuk, 1967; Allen, 2009) and mechanics and engineers (Hanlon, 2022), though these measures are also potentially outcomes of mills' steam adoption; differences in capital availability through banks (Jaremski, 2014);[45] and all of the above controls.

[43] Rows 2, 3, and 4 include additional controls for county access to coal (in addition to our baseline controls that include an indicator for any workable coal in the county, the share of the county covered by workable coal deposits, and access to workable coal deposits via the transportation network). Row 2 includes controls for if in the 1850 Census of Manufacturing the county reports any coal mining, the arcsin of coal mining production in dollars, and the lowest transportation cost to the closest coal producing county. Row 3 includes separate controls for each type of coal deposit (lignite, subbituminous, bituminous, and anthracite). Row 4 controls for a cubic polynomial in the share of the county covered by workable coal deposits.

[44] Because different access to material inputs may have influenced flour and lumber mills' steam adoption (Nurkse, 1953), row 5 controls for county wheat suitability (from FAO-GAEZ data provided by Rusanov 2021) and row 6 controls for share of the county covered by woodland (as in Hornbeck 2010).

[45] Rows 7–9 control for county access to labor and capital inputs: row 7 controls for local wages in manufacturing in the Census data (Allen, 2009); row 8 controls for the share of county population who report

In Appendix Table A.8, we show that our results are robust to other adjustments to our controlling for features of counties' economic environment. First, we show our results are robust to removing some or all of our controls for access to markets or coal.[46] Our results are robust to controlling for time-varying market access and population, which are themselves potentially endogenous to steam adoption, or growth associated with counties' fixed 1850 population.[47] Some estimates are smaller when controlling for population, but this also introduces bias because county population is endogenous to local waterpower potential (even in 1850). Our results are robust to controlling for alternative sources of potential growth: an indicator for being in Appalachia or on the frontier (Bazzi, Fiszbein and Gebresilasse, 2020), the share of workers in agriculture (Eckert and Peters, 2023), having a portage site (Bleakley and Lin, 2012),[48] exposure to the Civil War,[49] and all of these time-invariant controls interacted with decade.

Appendix Table A.9, Column 1, shows that counties with lower waterpower potential experienced faster population growth during this period (7% to 10% per decade), but population is not driving our estimates on steam adoption. While counties with lower waterpower potential had a higher share of mills using steam power in 1850 (Table 3), they had lower population in 1850 (Appendix Table A.9). Further, Appendix Table A.9 shows that lower water power counties experienced increases in milling activity even in per capita terms. Our

being engineers or mechanics (Hanlon, 2022); row 9 controls for the number and total capital of local banks (Jaremski, 2014).

[46]Rows 2–4 use subsets of our baseline controls: row 2 excludes our baseline controls for market access and navigable rivers; row 3 excludes our baseline controls for coal; and row 4 excludes both sets of controls.

[47]Row 5 controls for contemporaneous market access. Row 6 controls for contemporaneous population. This is itself an endogenous outcome to waterpower availability and the arrival of steam power, so this is not our preferred specification, and rows 7–12 alternatively control for time-invariant county characteristics (interacted with year), which adjust for potentially differential growth patterns across counties with different waterpower potential, though even 1850 county outcomes are influenced by county waterpower potential.

[48]Row 11 controls for whether counties had historical portage sites, which was less directly relevant by our sample period but had persistent path-dependent effects on economic activity (Bleakley and Lin, 2012). Conceptually, there are two differences between waterpower potential and portage sites, which create independent variation in the two. First, portage sites were on navigable rivers, whereas local waterpower potential can also come from non-navigable rivers. Second, portage sites reflect any discrete changes in elevation, whereas waterpower potential varies more continuously in terrain ruggedness. For example, the St. Anthony Falls in Minneapolis has a elevation change of 49 feet, almost double the height of the Falls of Ohio by Louisville. Both were portage sites, but the former was more useful for water power.

[49]Feigenbaum, Lee and Mezzanotti (2022) note that Sherman's troops explicitly targeted lumber mills. Following their identification strategy, we confirm in our data that counties affected by Sherman's March experienced a decline in lumber mills. We also find that the survival rate fell. We do not find an effect on switching for the water incumbents, but we have limited data on affected counties with surviving mills (since the manuscripts for Georgia were lost). Row 12 includes controls for differential exposure to the Civil War, following Hornbeck and Rotemberg (2024): whether there was a battle in the county; the number of battles; the total number of casualties; an indicator for if the number of casualties was over 500; if the county was on the Union/Confederacy border; if the state had legal slavery in 1864; if the state seceded from the union; and the share of industrial activity in broadly war-related industries.

estimates from Table 5 are also inconsistent with population growth driving our results: if county growth were being driven by more customers, it would be difficult to rationalize the decreased survival of incumbents.

Our analysis focuses on county-level geographic variation in waterpower availability, though there could also potentially be within-county differences in location advantages for steam power. One salient locational characteristic could be the distance to the closest railroad, which was a source of fuel imported from other counties. We digitized historical maps of railroad station locations, and found locational variation within and between counties. Some counties had water power sites close to stations and in others they are far away, which could lead to differences across water incumbents in the feasibility of switching to steam power and therefore a potential source of technological lock-in. Nevertheless, Appendix Table A.10 shows that distance to railroad station is not an additional substantive source of variation in steam suitability: it does not predict steam-use, water incumbents switching to steam, or a differential response of entrants versus incumbents.

C.2.2 Robustness to Sample Restrictions

Our main analysis restricts the sample to the panel of counties with at least one mill in 1850. In Appendix Table A.11, we show that our results are similar when including different sets of counties: expanding the sample to include all counties that ever had a mill, or limiting the sample to counties with multiple mills in 1850.[50] Our estimates are also not sensitive to dropping large county groupings, made in the construction of geographically-consistent counties, which potentially misclassify local waterpower availability, or the counties with extreme local waterpower potential.[51] Our results are also similar if we exclude counties that were more involved with cross-county or international trade in mill output: the 20 largest cities at the time, or places that Kuhlmann (1929) describes as having "merchant mills" that exported their output.[52]

C.2.3 Robustness to Measurement and Linkage Error

A natural question is how much our estimates might be affected by measurement error, particularly errors in the construction of our panel links. Our main results use time-intensive

[50]Row 2 expands the sample to an unbalanced panel of all counties that ever had a mill in our sample period. Rows 3 and 4 constrain the sample to counties that had at least 3 or 5 mills in 1850, which are counties that are substantially less likely to report no mills in subsequent decades. When we limit the sample to at least 3 mills or 5 mills in 1850, we exclude 94 and 175 counties, respectively.

[51]Our baseline sample drops the two grouped counties with areas larger than a circle with a radius of 50 miles, and row 5 shows that results are similar when we include them. Rows 6 and 7 exclude counties with extreme values of measured waterpower potential: row 6 drops the 1% largest and smallest values, and row 7 drops the 5% largest and smallest values.

[52]Row 9 drops Baltimore, Buffalo, Chicago, Cincinnati, Cleveland, Milwaukee, Minneapolis, Oswego, Philadelphia, Richmond, Rochester, St. Louis, and Washington DC.

hand-links, but there are inevitably false negatives and false positives in the links. To create a measure of confidence for any given link, we use the estimated linking probabilities from the supervised machine learning algorithm trained on the hand-links. We use this to explore the quality of hand-links, along with the sensitivity of our estimates to adding panel mills that were almost linked or removing those for whom the links are less predictable.

Appendix Figure A.4, Panel A, shows the predicted match probability for the hand-links. For mills whose sector and ownership structure were unchanged from one decade to the next, the hand-links are very predictable: most match probabilities are above 0.8. For mills that changed milling sector (e.g., flour-to-lumber), and especially for mills that gained or lost some owners, the match probabilities are lower but still mostly above 0.5. For our regression analysis, a primary concern would be that linkage errors are correlated with county waterpower potential. Appendix Figure A.4, Panel B, shows that the distributions of predicted match probabilities are similar for mills in counties with low and high waterpower potential.

One advantage of the ML model for robustness analysis is that we can change the matching cutoff, which mechanically changes the firm survival rate along with the rate of false-negative and false-positive matches. Appendix Figure A.15 shows how raising the cutoff lowers the share of ML links that are not hand-links (the "false match" rate, akin to a false discovery rate) but also lowers the share of hand-links that are made by the ML model (the "found match" rate, akin to the sensitivity).[53] Most hand-links (67%) are also predicted by the ML model. Conditional on finding a match, it is rare that the ML-links and hand-links disagree on the identity of the match.

Appendix Tables A.13 and A.14 compare entrant and incumbent outcomes, which are the estimates most likely affected by linkage errors. Appendix Table A.13 shows how the entry rate (Columns 1–3) and incumbent survival rate (Columns 4–6) vary with county waterpower potential, in each decade. Appendix Table A.14 shows results for steam use by entrants (Columns 1–3) and water incumbents (Columns 4–6).

Our results are similar if we restrict our panel sample to those mills linked by hand *and* the baseline ML model, rather than our main sample of hand-links, or use *only* the benchmark ML-links and raise or lower the benchmark cutoff for classifying matches.[54] Our

[53]Our machine-learning links use a predicted match probability of 0.4 as the benchmark cutoff for classifying a mill as surviving from one decade to the next, which is close to maximizing the "found match" rate while keeping the "false match" rate relatively low. Appendix Table A.12 shows that with this cutoff, the survival rate is higher using the ML-links (compared to the hand-links), as many mills are only classified as surviving using the ML model.

[54]Our benchmark ML model considers mills linked across decades if they have a match probability of at least 0.4. In row 2, we limit the panel links to only mills that are matched *both* by hand and by the benchmark ML model. In row 3, we use only the benchmark ML links. Row 4 restricts the matches to those

estimates are also similar when considering each type of mill separately: those classified with a "business name" (e.g., "Rock Creek Mill") or named after their proprietors, and might therefore be differentially subject to linkage error.

Our baseline regression sample includes mills who report positive sales, regardless of their input costs, though we further limit the sample to mills who report all inputs to calculate the elasticity of substitution. Rows 8 and 9 show that our regression results are robust to these sample choices: row 8 restricts the sample to mills who report all inputs, and row 9 expands the sample to include the mills with unreported output (who were likely inactive at the time). Finally, row 10 includes mills that do not explicitly report using water or steam power, where we consider a mill as steam powered only if it explicitly mentions steam.

D Model Details

D.1 Stylized Model

This Appendix section provides details on the stylized model from Section I.

D.1.1 Productivity Cutoffs

This subsection characterizes the productivity cutoffs that determine power adoption choices in Figure 1. To solve for these cutoffs, we define a few additional parameters: the demand curve faced by each firm is $q(p) = B\,p^{-\sigma}$, they pay a wage rate w for the variable input, and the survival probability is δ.

A firm of productivity φ using power technology $R \in \{W, S\}$ earns profits:

$$\pi_R(\varphi) = \kappa \exp\big[(\sigma-1)\big(\varphi+\gamma_R\big)\big], \tag{11}$$

where $\kappa \equiv \frac{B}{\sigma}\left(\frac{\sigma-1}{\sigma}w\right)^{\sigma-1}$.

For a given firm, the gap in flow profits for steam verses water are:

$$\Delta\pi(\varphi) = \pi_S(\varphi) - \pi_W(\varphi) = \kappa^* e^{(\sigma-1)\varphi}, \tag{12}$$

where $\kappa^* \equiv \kappa\left[e^{(\sigma-1)\gamma_S} - e^{(\sigma-1)\gamma_W}\right]$.

There are five thresholds that partition the productivity space into regions of technology choice by region.

with a ML-link probability of 0.6, and row 5 expands the matches to those with a ML-link probability of at least 0.2. Rows 2–5 change the survival and entry rates, mechanically, but do not qualitatively change the relationship between waterpower potential and entry or survival.

Cutoff for using water:

$$\bar{\varphi}_2^W = \frac{1}{\sigma - 1}\left[\ln\left(\frac{c_W}{(1+\delta)\kappa}\right) - (\sigma - 1)\gamma_W\right]$$

Cutoff for using steam, Period 3 entrants:

$$\bar{\varphi}_3^L = \frac{1}{\sigma - 1}\ln\left(\frac{c_3(S) - c_W}{\kappa^*}\right)$$

Cutoff for using steam, Period 2 entrants:

$$\bar{\varphi}_2^L = \frac{1}{\sigma - 1}\ln\left(\frac{c_2(S) - c_W}{(1+\delta)\kappa^*}\right)$$

Cutoff for switching to steam, Period 3 water incumbents:

$$\bar{\varphi}_3^S = \frac{1}{\sigma - 1}\ln\left(\frac{c_3(S) + c(W,S)}{\kappa^*}\right)$$

Cutoff for switching to steam, Period 2 water incumbents:

$$\bar{\varphi}_2^S = \frac{1}{\sigma - 1}\ln\left(\frac{c_2(S) - \delta\, c_3(S) + (1-\delta)c(W,S)}{\kappa^*}\right)$$

D.1.2 Illustrative Parameterization

We illustrate the stylized model in Figures 1 and 2, using illustrative parameter values. As the model is not quantitative in nature, nor calibrated to empirical targets, these values should not be given intrinsic interpretation. For illustration, the chosen parameter values are: $\gamma_W = 0$, $\gamma_S = 0.5$, $c(W) = 2$, $c_2(S) = 200$, $c_3(S) = 80$, $c(W,S) = 300$, $\delta = 0.1$, $B = 0.9$, $\delta = 0.1$, $w = 1$, $\sigma = 5$, $Var(\varphi) = 0.25$, $\bar{\varphi} = 1.8$.

D.2 Quantitative Model

This Appendix section provides details on the quantitative model from Section IV.

D.2.1 Modeling the Arrival of Steam Power

We initiate the model in 1830, before steam power became broadly available to mills in the US (Woodbury Report, 1838). We assume the economy was in a steady state before steam, with differences across counties reflecting their different water costs. In 1830, firms receive news that steam will become increasingly available. After that surprise, firms have perfect foresight about the path of falling steam costs.[55] Steam power first becomes purchasable at a high price in 1830, and its fixed adoption cost then monotonically declines until reaching its steady-state level around 1900.[56]

The falling steam cost is the only driving force along the transition path. We assume water technology is unchanged over this period, as it was a comparatively mature technology. Indeed, Rosenberg and Trajtenberg (2004) estimate that horsepower per waterwheel was largely stable over time.

D.2.2 Solution Algorithms

The equilibrium for each economy is a complicated fixed point: heterogeneous firms make forward-looking decisions about entry, exit, and power adoption, and firms' decisions are interlinked through their competition in local product markets and agglomeration spillovers in steam power choices. We study the transition path of the economy, where falling steam costs drive the transition from water to steam power.

This section describes our solution algorithms. In Section D.2.3, we show how we solve firms' dynamic programs by combining value function iteration (in the steady states) with backward recursion (along the transition path). In Section D.2.4, we describe how we solve the dynamic equilibrium using a fixed-point shooting algorithm in the aggregate state variables.

D.2.3 Solving Firms' Dynamic Programs

We solve firms' dynamic programs by combining value function iteration (in the steady states) with backward recursion (along the transition path).

The expected operating values, $\mathbb{E}_\varepsilon[V^o_{ct}(R,\varphi)]$, are the key determinant of firms' forward-looking decisions. Once firms know the operating values, their optimal decisions about entry, exit, and power adoption are only determined by contemporaneous features of the economy.

The expected operating values satisfy the Bellman equation:

$$\mathbb{E}_\varepsilon[V^o_{ct}(R,\varphi)] = \mathbb{E}_\varepsilon \max_{R'} \left\{ \begin{array}{l} \pi_{ct}(R',\varphi) - c_{ct}(R,R') - \varepsilon_{jct}(R') \\ + \delta \mathbb{E}_{(\varphi'|\varphi)} \mathbb{E}_\nu \max \left\{ \mathbb{E}_\varepsilon \left[V^o_{ct+1}(R',\varphi') \right] - f^{R'}_o - \nu^{R'}_{jct}(0), \Omega^{R'}_{ct} - \nu^{R'}_{jct}(1) \right\} \end{array} \right\}. \tag{13}$$

Equation (13) involves two maximization steps over distributions of idiosyncratic cost shocks (for adoption ϵ and operation/exit ν, respectively). The parametric assumptions in Section IV.B simplify these steps. In particular, when the cost shocks follow Gumbel

[55] Humlum (2022) adopts a similar approach to modeling the arrival of robots in modern manufacturing. While we do not have measures of millers' expectations, contemporaneous accounts of steam technology are consistently optimistic about the potential for future improvements (e.g., Scientific American 1869).

[56] Steam power reached its peak adoption in US manufacturing around 1890-1900 (Jovanovic and Rousseau, 2005), prior to the large-scale arrival of electricity in milling (Fenichel, 1966).

distributions, Equation (13) simplifies to a log-sum expression for the expected maximum (EMAX) (Train, 2009; Keane, Todd and Wolpin, 2011):

$$\mathbb{E}_{\varepsilon}[V^{o}_{ct}(R,\varphi)] = \rho \log \left[\sum_{R'} \exp \left\{ \frac{1}{\rho} \left(\pi_{ct}(R',\varphi) - c_{ct}(R,R') + \delta \mathbb{E}_{(\varphi'|\varphi)} \rho_o \log \left[\exp\left(\frac{\mathbb{E}_{\varepsilon}\left[V^{o}_{ct+1}(R',\varphi')\right] - f^{R'}_{o}}{\rho_o} \right) + \exp\left(\frac{\Omega^{R'}_{ct}}{\rho_o} \right) \right] \right) \right\} \right]. \tag{14}$$

We use the recursive scheme in Equation (14) to solve for the expected operating values in the steady states and along the transition path. To do so, we discretize the productivity process using the Tauchen (1986) method on 100 grid points. We assume that firms have perfect foresight about the price index and steam share (our two aggregate state variables) up to unanticipated aggregate shocks to the economy (e.g., the first arrival of steam power).

D.2.3.1 Steady State. Equation (14) is a contraction mapping when operating values are stationary, $\mathbb{E}_{\varepsilon}[V^{o}_{ct+1}(R,\varphi)] = \mathbb{E}_{\varepsilon}[V^{o}_{ct}(R,\varphi)]$, so we can solve for the unique fixed point $\mathbb{E}_{\varepsilon}[V^{o}_{ct}(R,\varphi)]$ by iterating on Equation (14) until convergence. Convergence of the value function iteration procedure is ensured by Blackwell's sufficient conditions for contraction mappings (Stokey, Lucas and Prescott, 1989, Theorem 4.6).

D.2.3.2 Transition Path. Starting from the terminal steady-state values, $\mathbb{E}_{\varepsilon}[V^{o}_{cT_1}(R,\varphi)]$, we solve for the operating values along the transition path $\{\mathbb{E}_{\varepsilon}[V^{o}_{ct}(R,\varphi)\}_{t=T_0}^{T_1-1}$ using backward recursion on Equation (14) from $T_1 - 1$ to the initial period T_0.

D.2.4 Solving the Dynamic Equilibrium of the Economy

We use a shooting algorithm that iterates on the time paths for the mass of operating firms and entrants to find a fixed point of the equilibrium policy functions. Convergence of our iterative algorithm is ensured by a congestion force in the product market. The convergence property also ensures that an equilibrium exists and tends to be unique, although strong agglomeration effects in steam adoption could lead to multiple equilibria that we consider directly.

D.2.4.1 Steady State. To solve for the steady-state equilibrium, we use a nested algorithm: the outer loop searches for the mass of entrants M_c that closes the free entry condition, and the inner loop iterates over the mass of operating firms $F_c(R,\varphi)$ to find a fixed point of the equilibrium policy functions for exit and power adoption. Our solution algorithm is:

1. Set an initial grid for the mass of entrants $\{M_c^{(0)}, M_c^{(1)}, M_c^{(2)}, ...\}$. For each grid point $(i) = 0, 1, 2, ...,$:

2. Solve for the equilibrium mass of operating firms $F_c^{(i)}(R,\varphi)$:

(a) Set an initial guess for the mass of operating firms $F_{ct}^{(i,0)}(R,\varphi)$. For each iteration $(j) = 0, 1, 2, ...,$:

(b) Solve for the expected operating values $\mathbb{E}_\varepsilon[V_{ct}^{o(i,j)}(R,\varphi)]$ by iterating on the contraction mapping in Equation (14).

(c) Simulate the mass of operating firms: given $F_{ct}^{(i,j)}$ and $M_{ct}^{(i)}$, use the policy functions for exit and power adoption to simulate the firm mass $F_{ct}^{(i,NEW)}(R,\varphi)$.

(d) Update the mass of operating firms:

$$F_{ct}^{(i,j+1)}(R,\varphi) = \lambda F_{ct}^{(i,NEW)}(R,\varphi) + (1-\lambda) F_{ct}^{(i,j)}(R,\varphi), \tag{15}$$

where $\lambda = 0.5$ is the relaxation parameter in the Gauss–Seidel update.

(e) Repeat Steps 2b–2d until $\sum_{R,\varphi} |F_{ct}^{(i,j+1)}(R,\varphi) - F_{ct}^{(i,j)}(R,\varphi)| \leq tol_F$ for a small tolerance level tol_F.

3. Evaluate the free entry condition:

   (a) Compute entry values $EV_{ct}^{(i)} = \mathbb{E}_\varphi\left[V_c^{(i)}(E,\varphi)\right]$ by plugging $\mathbb{E}_\varepsilon[V_c^{o(i)}(R,\varphi)]$ into the exit rule and integrating over the stationary distribution for φ.

   (b) Compute the deviation from the free entry condition: $\mathcal{F}_c^{(i)} = EV_c^{(i)} - f^e$.

4. Update the mass of entrants $M_c^{(i+1)}$ to set the predicted free entry condition to zero. We use a linear interpolation based on the previous iterations $\{M_c^{(k)}, \mathcal{F}_c^{(k)}\}_{k=0}^{i}$.

5. Repeat Steps 2–4 until $|\mathcal{F}_c^{(i)}| \leq tol_M$ for a small tolerance level tol_M.

We solve for the initial steady state ($T_0 = 1830$) and the terminal steady state (after $T_1 = 1900$). In the initial equilibrium, water power is the only available power source, which we model with a prohibitively high cost of steam adoption $c_{T_0}(S)$. In the terminal equilibrium, the cost of steam power has reached its new steady-state level.

D.2.4.2 Transition Path. We simulate a transition over T periods in which heterogeneous firms make forward-looking decisions about entry, exit, and power adoption, as steam costs are falling over time, and their decisions are interlinked through competition in product markets and agglomeration spillovers in steam power. As before, we use a nested shooting algorithm.

Let $\mathcal{F}(M)$ denote the vector of free-entry residuals across time given a path of entrants $M = \{M_{ct}\}_{t=T_0}^{T_1}$. We use a coarse-to-fine Newton method on M: starting on coarse time blocks and refining to the full grid, we compute a regularized Gauss–Newton/Tikhonov step

(Levenberg–Marquardt style) that penalizes high-frequency variation in M. Specifically, at a given resolution, we solve

$$\min_{\Delta M} \tfrac{1}{2}\big\|\mathcal{F}(M) + J_{\mathcal{F}}(M)\,\Delta M\big\|^2 \;+\; \tfrac{\lambda_{\text{smooth}}}{2}\big\|L\,(M+\Delta M)\big\|^2, \tag{16}$$

where L is a second-difference matrix over time and λ_{smooth} is an adaptive weight that decreases as $\|\mathcal{F}\|$ shrinks. This yields the stacked linear system

$$\begin{bmatrix} J_{\mathcal{F}} \\ \sqrt{\lambda_{\text{smooth}}}\,L \end{bmatrix} \Delta M = -\begin{bmatrix} \mathcal{F} \\ \sqrt{\lambda_{\text{smooth}}}\,L\,M \end{bmatrix}, \tag{17}$$

which we solve directly as a stacked least-squares problem using LSQR with column scaling (QR fallback). We then update

$$M \leftarrow M + \eta\,\Delta M, \tag{18}$$

with a damping factor $\eta \in (0,1]$ to mitigate overshooting. The time-block continuation proceeds over increasingly fine partitions and jumps early to the full grid if the full-path residual is already small.

Our solution algorithm follows the steps:

1. Set an initial guess for the mass of entrants $M_{ct}^{(0)}$. For each iteration $(i) = 0, 1, 2, ...,$:
2. Solve for the equilibrium mass of operating firms $F_{ct}^{(i)}(R,\varphi)$:
   (a) Set an initial guess for the mass of operating firms $F_{ct}^{(i,0)}(R,\varphi)$. For each iteration $(j) = 0, 1, 2, ...,$:
   (b) Solve for the expected operating values $\mathbb{E}_{\varepsilon}[V_{ct}^{o(i,j)}(R,\varphi)]$ by backward recursion on Equation (14) from the terminal steady state.
   (c) Simulate the mass of operating firms: given $F_{ct}^{(i,j)}$ and $M_{ct}^{(i)}$, use the policy functions for exit and power adoption to simulate the firm mass $F_{ct}^{(i,NEW)}(R,\varphi)$.
   (d) Update the mass of operating firms:

   $$F_{ct}^{(i,j+1)}(R,\varphi) = \lambda F_{ct}^{(i,NEW)}(R,\varphi) + (1-\lambda)F_{ct}^{(i,j)}(R,\varphi), \tag{19}$$

   where $\lambda = 0.5$ is the relaxation parameter in the Gauss–Seidel update.
   (e) Repeat Steps 2b–2d until $\sum_{R,\varphi,t} |F_{ct}^{(i,j+1)}(R,\varphi) - F_{ct}^{(i,j)}(R,\varphi)| \le tol_F$.
3. Evaluate the free entry condition:

(a) Compute entry values $EV_{ct}^{(i)} = \mathbb{E}_{\varphi}\left[V_{ct}^{(i)}(E,\varphi)\right]$ by plugging $\mathbb{E}_{\varepsilon}[V_{ct}^{o(i)}(R,\varphi)]$ into the exit rule and integrating over the stationary distribution for φ.

(b) Compute the deviations from the free entry condition:

$$\mathcal{F}_{ct}^{(i)} = EV_{ct}^{(i)} - f^e. \tag{20}$$

4. Update the path of entrants M by solving the regularized Newton system in (17) and applying the damped step $M \leftarrow M + \eta\,\Delta M$. Proceed to the next time-block resolution until the full grid is solved. Stop when $\max|\mathcal{F}(M)| \leq tolM$ (i.e., the $\ell\infty$ norm).

To prevent "end-of-horizon sprints" in the dynamic model, we simulate ten additional ghost periods (effectively setting $T_1 = 1910$ in our model simulations). As a consistency check, we verify that the mass of operating firms has reached its terminal steady-state value by T_1.

D.2.4.3 Counterfactual Policies. To evaluate policy counterfactuals, we first simulate the baseline economy. At the policy announcement date, we re-solve the dynamic equilibrium forward, using the preceding baseline equilibrium as initial conditions. The Levenberg–Marquardt regularization in Equation (16) performs well for smooth counterfactuals. However, for highly discontinuous cases (i.e., large shocks that cause the mass of entrants to shift sharply), such as the policies analyzed in Section V.D, the regularization can lead to excessive smoothing, preventing the solver from fully closing the free-entry condition. To address this, we allow the solver to switch to unregularized Newton steps (with Armijo-like backtracking) for specific time blocks if two conditions are met: (i) the regularized solver is stuck, and (ii) the counterfactual steam adoption rate deviates from the baseline simulation.

D.2.4.4 Approximate Path of Entrants. The algorithm for finding the path of entrants is computationally demanding, so we aid our algorithm with an approximation method that works well when the economy is transitioning smoothly between two known steady states (as in our baseline simulations). We use the approximation as starting values in Step 1, which eases the computational burden.

Our approximation is based on knowledge that: (1) the economy transitions smoothly between the steady states, and (2) the only driving force along the transition path is a steadily falling steam cost. We know that lower steam costs induce more entry, more steam adoption, and a lower price index. Hence, we search for a transition path where the mass of entrants evolves smoothly between the steady states:

$$M_{ct}(\xi) = \exp\left(\log M_{cT_0} + \left(\frac{t - T_0}{T_1 - T_0}\right)^{\xi} (\log M_{cT_1} - \log M_{cT_0})\right) \quad t \in [T_0, T_1], \tag{21}$$

where $\xi > 0$ governs the speed of convergence to the terminal steady state. Our goal is to find the value ξ^* that satisfies free entry and the other equilibrium conditions.

(i) Set an initial grid for the mass of entrants $\{\xi_c^{(0)}, \xi_c^{(1)}, \xi_c^{(2)}, ...\}$. For each grid point $(j) = 0, 1, 2, ...,$:

(ii) Perform Steps 2–3 in solving the transition path, for each value of $\xi^{(j)}$.

(iii) Update the parameter $\xi^{(j)}$ to set the predicted free entry condition to zero, using a linear interpolation based on the previous iterations $\{\xi^{(k)}, \mathcal{F}_c^{(k)}\}_{k=0}^{j}$.

(iv) Repeat Steps (ii)–(iii) until $|\sum_t \mathcal{F}_{ct}^{(j)}| \leq tol_M$.

This approximation for the path of entrants $M_{ct}(\xi^*)$ performs well in our baseline simulations: the mean absolute deviation of the free entry condition $\mathcal{F}_{ct}^*$ is less than 0.005% of average firm sales. The approximation algorithm takes 3 seconds to solve the baseline equilibrium, compared to 287 seconds for the exact algorithm. This savings in computational time is valuable because the equilibrium needs to be solved and simulated many times at various parameter values. We use the approximate path of entrants when estimating the model in Section IV.D, whereas the versatility of the exact algorithm is useful when evaluating the counterfactuals in Section V that hold most parameter values fixed.

D.2.5 Existence and Uniqueness of Equilibrium

D.2.5.1 Existence. Our iterative algorithm converges, and an equilibrium exists, because competition between firms in product markets creates a congestion force summarized by the price index P_{ct}. For intuition, we describe a few examples of how this congestion force operates.

First, suppose entry values exceed the fixed entry cost at our initial guess. More firms will enter the market, which lowers the price index P_{ct} and lowers profits, bringing down the value of entry.

Similarly, suppose the optimal survival rates exceed our initial guess. More firms will stay in business, lowering the price index P_{ct}, which decreases operating values and survival rates.

Finally, suppose the optimal steam adoption rates exceed our initial guess. More firms will adopt steam power, which lowers the price index P_{ct} (because steam has lower marginal costs), which decreases steam adoption (because of profit complementarities between steam power and the price index: $\frac{\partial \pi_{ct}(S,\varphi)}{\partial P_{ct}} > \frac{\partial \pi_{ct}(W,\varphi)}{\partial P_{ct}}$ when steam has lower marginal costs).

In summary, the convergence of our solution algorithm draws on this monotone relationship between the price index and the mass of operating firms (and steam users): a higher price index induces more entry and survival (and steam use), which in turn lowers the price index.

D.2.5.2 Uniqueness. The monotone relationship between the price index and the mass of operating firms (and steam users) also pushes toward there being a unique equilibrium, if the agglomeration force from steam is not sufficiently strong.

Suppose, for the sake of contradiction, that the economy could sustain two equilibria with different masses of entrants. The price index in the "low entry" equilibrium would then be higher, all else equal. But that higher price index would induce more entry, contradicting its "low entry" nature.

There could be multiple equilibria, however, with a sufficiently strong steam agglomeration force (i.e., a very positive α_S or very negative κ). For example, suppose that the agglomeration force is so strong that a higher steam share s_{ct} makes even more mills want to adopt steam (i.e., $\frac{d\pi_{ct}(S,\varphi)}{ds_{ct}} \geq \frac{d\pi_{ct}(W,\varphi)}{ds_{ct}}$). In this case, the economy could have a "low steam" equilibrium (where few mills adopt steam because there is little agglomeration benefit from the small number of other steam users) and a "high steam" equilibrium (where many mills adopt steam because there is a large agglomeration benefit from many others using steam).

This potential for multiple equilibria is largest when steam is most available, so more firms are at the margin of steam adoption. We check for multiple equilibria in our terminal steady state, when steam power is most available, by initiating our solution algorithm at different starting values for the equilibrium steam share (from 0% to 100%). The solution algorithm converges to our baseline equilibrium for all initial values, indicating that our estimated agglomeration force is not sufficiently strong to overcome the congestion force from the price index. Consistent with this uniqueness, we do not find persistent impacts on steam-use in counterfactuals that temporarily decrease the cost of adopting steam (even those that temporarily raise steam adoption to well above its steady-state usage).

D.3 Structural Estimation

We use the Method of Simulated Moments (MSM) to estimate the structural model, targeting within-county moments and between-county moments.

D.3.1 Target Moments

D.3.1.1 Within-County Moments. We match within-county moments in the model to the predicted values in year t for a baseline county B with average waterpower potential, denoted Y_{Bt}. We have data on two sectors (flour mills and lumber mills), while the model considers one composite milling sector. To construct this composite milling sector, we first calculate the relevant moment Y_{ict} for lumber and flour mills separately. We then estimate Y_{Bt} as a weighted average of the moment across lumber and flour mills in a county with average waterpower potential, predicted using our reduced-form specification in Equation (1).[57] That is,

$$Y_{Bt} \equiv \mathbb{E}_i \left[\mathbb{E}_c[Y_{ict}]\right] = \mathbb{E}_i \left[\gamma_{it}{}'\mathbb{E}_c[X_{ic}]\right], \tag{22}$$

where X_{ic} consists of our baseline controls, our standardized measure of local waterpower potential, and an industry fixed effect.

D.3.1.2 Between-County Moments. For between-county moments, we compare outcomes in the baseline county to outcomes in a county L with one standard deviation lower waterpower potential. The counterfactual moments for county L are identified under the assumption that local waterpower potential is a cost-shifter for local firms' use of water power, conditional on our included control variables. To estimate outcomes in county L, we follow Equation (22) but predict outcomes for a county with one standard deviation lower waterpower potential and hold all other characteristics fixed at their average levels. The difference in moments between county B and county L corresponds to our estimated reduced-form impacts of lower waterpower potential, $\hat{\beta}_t$.

D.3.2 Estimation Procedure

We estimate the structural model using a Newton-Rhapson algorithm that iteratively adjusts the parameter values $\theta \in \mathbb{R}^K$ to match model-simulated moments $f(\theta) \in \mathbb{R}^K$ to their target values $y^* \in \mathbb{R}^K$.

Starting from an initial value θ_0, the Newton method updates the parameter estimates as follows:

$$\theta_{n+1} = \theta_n - \lambda J_f(\theta_n)^{-1}(f(\theta_n) - y^*), \tag{23}$$

where $J_f(\theta_n)$ is the Jacobian of the moment function f, evaluated numerically around θ_n, and $\lambda = 0.5$ is a dampening parameter that mitigates overshooting and ensures stable convergence to the target values. This method works well when: (1) parameters and moments have smooth relationships (especially linear), such that J_f does not change too rapidly, and (2) the parameters have distinct mappings to each target moment (especially one-to-one), such that J_f is well-conditioned and non-singular. We discuss below the intuitive mapping between particular parameters and moments in theory, along with formally characterizing which moments connect most closely to particular parameters in practice.

We make three adjustments to the estimation procedure to ensure the regularity conditions are met robustly. First, we estimate the baseline productivity process (π, σ) and entry

[57] We weight by the number of mills in each county-industry.

costs f^e in an initial step to match their target moments before the arrival of steam power. Second, we implement an adaptive grid search in the steam production parameters (γ, f_o^S), executing the Newton method on each grid point. Third, we adopt a dimensional continuation strategy for our Newton method, gradually incorporating more parameter-moment pairs into the estimation problem:

(a) *Steam adoption within regions:* estimate $c_S^{(initial)}, c_S^{(terminal)}, c(R, R')$ to match their target moments.

(b) *Steam adoption between regions:* add $(c_L(W), \kappa)$ and their target moments to the estimation problem.

(c) *Output between regions:* add (α_S, η) and their target moments to the estimation problem.

(d) *Startup and fixed costs*: add (f_o^E, f_o^W) and their target moments to the estimation problem.

Our estimation algorithm only proceeds to the next step once the incorporated moments are sufficiently close to their target values. These adjustments ensure that our estimation algorithm is well-behaved. We validate that J_f has the signs and magnitudes predicted in theory at all iterations n.

D.3.3 Parameter Estimates and Related Moments

While we estimate the parameters jointly, there is often an intuitive mapping between particular parameters and moments. This section discusses the parameter estimates and their related moments from Table 7 and, when possible, compares the estimated magnitudes to evidence from contemporaneous sources and modern literature.

D.3.3.1 Establishment-Level Parameters and Within-County Moments We identify the micro-level parameters of production, entry, and power adoption by comparing the choices and outcomes of establishments within counties.

Steam productivity. A higher γ means that steam is relatively more productive, and consequently, steam users will have higher sales. We therefore use the sales differential between steam and water users within each county, as in Figure 4, to help identify γ. The observed difference in sales between steam and water users also reflects selection, as productive mills are more likely to use steam power, and we model this selection directly and account for it when estimating γ jointly with the other parameters.

The steam productivity premium, γ, lowers marginal production costs by about 8.9%. This structural estimate falls within the range of existing estimates of the efficiency of steam engines vs. waterwheels in the 19th century (Atack, 1979; Crafts, 2004; Chernoff, 2021).

Baseline productivity process. We estimate the persistence of the baseline productivities π using the 10-year auto-correlation of log sales at the establishment level (0.4). To help estimate the dispersion of productivities σ, we use the standard deviation of log sales within each county (1.0).

Our estimated parameters for π and σ are 0.9677 and 0.0897, which are within the standard range of estimates from modern data (Bachmann and Bayer, 2014; Coşar, Guner and Tybout, 2016; Schaal, 2017; Ottonello and Winberry, 2020). For example, Bachmann and Bayer (2014) estimate π and σ to be 0.9675 and 0.0905.

Operating costs. Given the dynamics of productivity, higher operating costs f_o^R will make firms more likely to exit. We therefore use the share of water (or steam) users that subsequently exit the market, as in Table 2, to help estimate f_o^R.

The operating costs of steam power f_o^S are larger than those of water power f_o^W, constituting 30% and 11% of 1850 median sales, respectively. Large operating costs of steam are consistent with the qualitative evidence that steam engines required more upkeep and reflect that steam users exit at a higher rate, despite being larger and more productive (as in Table 2 and Figure A.13). Our estimates are somewhat higher than contemporary estimates: Swain (1888) estimates that the annual fixed costs of steam and water power, respectively, were around \$20 and \$10 dollars per horsepower, which applied to 1850 firm medians are around 16% and 8% of annual sales.

Startup costs. Entrants have to pay $f_o^R = f_o^E + c(R)$ to start producing. A higher startup cost toughens the selection upon entry, increasing the relative sizes of entrant mills. We use the sales differential between incumbents and entrants (as in Figure 4) to help pin down f_o^R.

The startup cost of setting up a watermill $f_o^E + c_B(W)$ is around 43% of annual sales. These inferred costs are close to the capital stocks of water users directly observed in our data, as the value of the capital stock of the average water mill in 1850 was 51% of annual sales.

A higher entry cost will deter mills from entering the market. We use the share of producers who are entrants, as in Table 1, to inform our estimate of the entry cost f^e.

Power adoption costs. We split the startup costs into general milling capital f_o^E and power-specific capital $c(R)$ by comparing water mills (who pay $f_o^E + c(W)$) to hand powered mills (who only pay f_o^E) in our data.[58] The capital premium for water users is 0.5 log points, implying $\beta = \frac{c(W)}{f^E + c(W)} = 0.4$.

A higher adoption cost of steam power relative to water $\tilde{c}_t(S) = c_t(S) - c(W)$ leads fewer firms to choose steam over water power. We use the share of establishments using steam power in 1850 and 1880, as in Figure 3, to help estimate $\tilde{c}_t(S)$.

Water power in the baseline region $c_B(W)$ had an upfront cost of around 433 dollars, equivalent to about 17% of 1850 median sales. Steam initially had a higher upfront cost, and we estimate that in 1850 the upfront cost of steam power $c_{1850}(S)$ was about 583 dollars or 23% of median sales. These estimates are broadly consistent with historical accounts, though they fall in the lower end of the reported range.[59]

We estimate that as steam became more available and adaptable, the upfront cost of steam fell below water, converging to a level of around 9% of annual sales. Emery (1883) reports that the purchase prices of steam and water power were similar in 1880, which is consistent with our estimates. The continued use of water power in this later period reflects lower operating costs, idiosyncratic shocks, and switching costs.

Power switching barriers. Higher power-switching barriers lead incumbents to switch power technologies less often. To help estimate the barriers that incumbents face to switch technologies, we use the within-county difference in adoption shares for entrants versus incumbents, as in Figure 3:

$$\log \frac{\Pr(R|R,\varphi)}{\Pr(R'|R,\varphi)} - \log \frac{\Pr(R|E,\varphi)}{\Pr(R'|E,\varphi)} = \frac{1}{\rho} \times \left(c(R,R') + (1-\omega^R)c_{ct}(R)\right). \tag{24}$$

We estimate that the total switching barrier from water (including sunk capital $(1-\omega^W)c(W)$ and other switching costs $c(W,S)$) constitutes 19% of 1850 median annual sales or just above two months' worth of revenue. Notably, fully sunk water capital ($\omega^W = 0$) can account for the vast majority of these switching barriers (93%), and the switching costs $c(W,S)$ only represent 1.4% of annual sales. Sunk steam capital ($\omega^S = 0$) similarly accounts for the majority (81%) of switching barriers from steam to water power, though we estimate larger costs of switching from steam to water, perhaps due to the importance of location for water power.

[58] We do not include hand-powered mills in our broader analysis, as these mills only constitute 0.6% of total revenue in flour and lumber milling.

[59] In our 1850 data, the typical water and steam mills had, respectively, around \$500 and \$2000 more capital installed than the hand-powered mills. Likewise, contemporaneous sources note that 20 horsepower engines – including the boiler and other associated equipment – cost \$2,500 in the 1840s and \$2,000 in the 1880s (Armistead, Lawson and Long, 1841; Emery, 1883; Atack, Bateman and Weiss, 1980). While our estimated fixed adoption costs are somewhat lower than these historical figures, our estimated operating costs are slightly higher than those reported in contemporaneous accounts.

D.3.3.2 County-Level Parameters and Across-County Moments The comparison across counties is crucial for identifying county-wide parameters, including the demand elasticity for milling and steam agglomeration forces.

Regional cost of water power. The additional fixed cost of water power in places with lower waterpower potential, $\tilde{c}_L(W) = c_L(W) - c_B(W)$, lowers the attractiveness of using water power. Therefore, we estimate it using the relationship between waterpower potential and the share of mills using water power (as in Table 3).

We estimate that the additional water cost in the low-water region $\tilde{c}_L(W)$, 95 dollars, is around a quarter of the cost in the baseline region. By comparison, Atack, Bateman and Weiss (1980) estimate that the average water-horsepower for all manufacturing in 1850 cost two-thirds more in the Midwest compared to New England.[60] One reason why our numbers might be smaller is that millers were relatively small power users, and therefore less affected by more-limited local water power.

Total demand elasticity. The total demand elasticity η determines how sensitive the demand for milling output is to milling prices. We use the initial (1850) relationship between lower waterpower potential (which increases milling costs) and local milling activity to identify η (as in Table 3). We estimate a total demand elasticity of 5.90, which suggests that local demand for milling is fairly elastic.

Agglomeration in steam adoption. An agglomeration force in steam adoption costs (negative κ) will further boost the adoption of steam power in the low-water region. Hence, to identify the agglomeration in power costs, we use the impact of lower water power on the take-up of steam power from 1850 to 1880, as in Table 4.

We estimate a κ that is economically close to zero. In particular, increasing the steam adoption rate from 0 to 100% slightly increases the adoption cost of steam power by 41 dollars. Appendix D.3.6.3 shows that forcing this parameter to zero (keeping other parameters fixed) does not affect equilibrium steam adoption rates.

Agglomeration in steam productivity. An agglomeration force in steam productivity (positive α_S) will boost economic growth in the low-water region (where steam is diffusing faster). Hence, to identify the agglomeration in steam productivity, we use the impact of lower water power on revenue growth from 1850 to 1880, as in Table 4.

We estimate an α_S that is modest for any individual establishment but generates substantial increases in aggregate output by inducing entry. In particular, increasing the steam adoption rate from 0 to 100% increases the productivity of steam power by 2.55%. Appendix

[60] On average, counties in the Midwest have around 1.1 standard deviations less waterpower potential than counties in New England.

D.3.6.3 shows that by forcing this parameter to zero, the model can only account for around half of the differential growth we observe in the low-water regions.

D.3.3.3 Calibrated Parameters We calibrate the following parameters outside the estimation routine.

Firm demand elasticity. In our model, mills charge a constant sales-to-cost markup $\frac{1}{\epsilon-1}$ over variable costs (materials and labor). In Appendix A.1, we calculate that the median sales-to-cost markup among flour and lumber mills is 20%, implying an elasticity of demand between individual mills of 6. In comparison, modern estimates range between 3 and 11 (Asker, Collard-Wexler and de Loecker, 2014; Bloom, 2009; Sedláček and Sterk, 2017; Felbermayr, Impullitti and Prat, 2018; Acemoglu et al., 2018; Buera et al., 2021), and are relatively large in milling (Broda and Weinstein, 2006).

Time discounting. The discount factor (denoted as δ) is calibrated to reflect an annual interest rate of 6%. In Section D.3.6.3, we support the forward-looking assumption by demonstrating that ignoring future returns (a scenario with $\delta = 0$) would imply an implausibly low estimate for the startup capital cost of milling.

Sunk costs. Our baseline setup assumes that the costs of water and steam capital are fully unrecoverable and set ω^R to zero. We think this is a reasonable assumption: because waterwheels and associated infrastructure such as dams and millponds were attached to a particular structure, it would be difficult for a miller to switch to steam and have a different mill use the waterpower. We explore robustness to partial irreversibility, however, and also evaluate counterfactuals where capital is instead partially recoverable.

Convergence rate for steam technology. The parameter $c_S^{(slope)}$ governs how fast steam adoption costs fall from their initial state $c_S^{(initial)}$ to their mature state $c_S^{(terminal)}$. We set the convergence rate to 4% per year, which implies that steam power matures by 1890. This assumption is consistent with the long-run diffusion patterns in Jovanovic and Rousseau (2005) and aligns with the power cost estimates presented in Atack (1979). We show that the estimated model can match the steam adoption patterns in all decades from 1850 to 1880, despite fixing the convergence rate to this literature-informed value.

Dispersion of cost shocks. We set the dispersion parameters ρ and ρ_o to 2, equivalent to about 6.5% of median 1850 sales. These values fall within the range of estimates in the literature (Chernoff, 2021; Humlum, 2022) and imply a limited amount of idiosyncratic variation in power and operation costs. As a validation of the amount of idiosyncrasies in power and exit choices, our estimated model can match the observed overlap between exiting and surviving firms (as in Figure 4) and the overlap in firm size distributions between steam and water users (as in Appendix Figure A.16).

D.3.4 Standard Errors

We compute standard errors for the structural parameter estimates $\hat{\theta} \in \mathbb{R}^K$ using the Delta method. Let $f(\theta) \in \mathbb{R}^K$ denote the vector of model-simulated moments, and let $J_f(\theta)$ denote its $K \times K$ Jacobian. We obtain the empirical covariance matrix of the sample moments, $\hat{\Omega}$, by bootstrapping the data and recomputing the moments across bootstrap samples.

The Delta-method variance of the parameter estimates is then

$$\widehat{\mathrm{Var}}(\hat{\theta}) = J_f^{-1}(\hat{\theta})\,\hat{\Omega}\left(J_f^{-1}(\hat{\theta})\right)'. \tag{25}$$

We compute the empirical covariance matrix $\hat{\Omega}$ using standard bootstrapping. In each iteration, we resample the county-industry data with replacement and compute the target moments. We repeat this procedure 500 times to obtain a set of estimates for each moment, from which we compute $\hat{\Omega}$. These standard errors are computed for the parameters estimated with our Newton-based procedure, which directly exploits the Jacobian (see Section D.3.2).

Appendix Table A.15 presents the estimates. Overall, our structural parameters are estimated with precision. The initially high fixed cost of steam is highly significant, as is its decline over time—the key force driving the transition path. By contrast, residual power-switching barriers beyond those from sunk capital are not statistically different from zero, implying that switching barriers reflect sunk capital investment. Water costs are significantly lower in low-water-power regions, underscoring the fundamental regional difference. Finally, the agglomeration spillover in steam productivity (α) is statistically positive, whereas we cannot reject the absence of agglomeration in steam adoption (κ).

D.3.5 Parameter Identification

This section conducts a formal analysis of our sources of parameter identification, following the local sensitivity measures proposed by Andrews, Gentzkow and Shapiro (2017), which support the above intuitive relationship between particular parameters and moments. This analysis also highlights the importance of estimating the model parameters jointly, however, as many parameters affect multiple target moments simultaneously.

We now analyze the local relationships between parameters and moments around the best-fit values θ^*. Appendix Tables A.16 and A.17 report two standard measures of parameter identification: (1) the Jacobian of the moment function, which captures how simulated moments change with parameter values,[61] and (2) the sensitivity measure of Andrews,

[61] The Jacobian is a commonly used diagnostic to assess the empirical properties of structural models (see, e.g., Berger and Vavra (2015); Ottonello and Winberry (2020); Balke and Lamadon (2022)).

Gentzkow and Shapiro (2017), which captures how estimated parameters change with target moments.[62]

We show these relationships for our Newton-based estimation, which relies directly on the Jacobian for the estimation. We order the table rows and columns such that the diagonal elements capture the relationship between parameters and their target moments, as discussed in Sections D.3.3.1 and D.3.3.2. Appendix Tables A.16 and A.17 yield four main insights into the identification of our structural model.

First, the simulated moments are highly sensitive to our parameters, which suggests that our parameters are identified. For example, increasing the water-to-steam switching costs by 1% of firm sales brings the incumbent-to-entrant steam switching rate 7 percentage points away from its perfectly fitted target values (see the third diagonal element of the Jacobian matrix).

Second, the Jacobian and sensitivity matrices have pronounced excess mass along their diagonals, which indicates a particularly strong link between model parameters and their target values. This suggests that the selected target moments are particularly important for identifying each of the parameters.

Third, reassuringly, all of the diagonal elements have the signs predicted by the discussed relationships between moments and parameters in Sections D.3.3.1 and D.3.3.2.

Fourth, the Jacobian and sensitivity matrices also have important off-diagonal elements, which highlight the importance of estimating the model parameters jointly. For example, Appendix Table A.17 shows that a higher water exit rate implies that steam costs must be higher to rationalize the observed level of steam adoption.

D.3.6 Model Validation

This section examines the validity of our estimated model. First, we show that the model can reproduce a series of non-targeted regressions on how waterpower potential shapes steam adoption and economic growth of incumbents and entrants. Second, we validate the assumed forward-looking behavior of establishments.

D.3.6.1 Non-Targeted Moments Appendix Table A.18 compares our reduced-form estimates from Tables 4, 5, and 6 to equivalent regressions on simulated data from our model.

Table 4 shows that higher water costs cause faster steam adoption, which Table 6 shows is driven by entrants. Over time, the effect of local waterpower potential diminishes.

Appendix Table A.18 shows our estimated model exhibits the same pattern. This is

[62]The sensitivity matrix M is related to the Jacobian J as follows: $M = (J'WJ)^{-1}J'W$, where W is a weighing matrix that does not matter in our exactly-identified case.

because higher costs of water affect steam adoption by making steam power a comparably cheaper technology (a *technology cost* effect), strengthening the selection of operating mills (a productivity *selection* effect), and weakening competition in local product markets (a *competition* effect). These effects are reinforced by an *agglomeration* effect in steam power. The *technology cost*, *selection*, *competition*, and *agglomeration* effects all lead to more steam use in places with higher water costs. Incumbents differ from entrants due to switching barriers, which make their steam adoption decisions less responsive to the cost of water power. Places with less waterpower potential approach their steady-state use of steam power earlier. As a result, along the adoption curve, the effect of waterpower potential on the *growth* in steam use diminishes and reverses over time, though in *levels* places with less waterpower potential are always more likely to use steam power.

Table 4 also shows that higher water costs cause faster revenue growth, which again Table 6 shows is driven by entrants.

Appendix Table A.18 also shows that our estimated model replicates this pattern. Higher costs of water increase the revenue growth from steam power through the *technology cost*, *selection*, and *agglomeration* channels described above. The *technology cost* and *agglomeration* benefits depend on mills' access to steam power, with diminished gains for water incumbents who face switching barriers. Incumbents are crowded out in places with higher water costs when the negative *competition* effect from new entrants is strong enough.

Finally, Appendix Table A.18 shows our estimated model is able to match two seemingly incongruous features of the data: that incumbents in places with lower waterpower potential are both (1) more likely to invest and switch to steam power (Table 6) and (2) more likely to exit (Table 5). This reflects countervailing forces that dominate in different parts of the firm-productivity distribution: incumbents in places with lower waterpower potential places are relatively high productivity, and this selection means that (all else equal) they are more likely to choose to switch to steam power. However, the increased entry and greater steam-use in places with lower waterpower potential lowers the local price index, which lowers survival rates for the marginal incumbents (of which there are more in places with less waterpower potential).

D.3.6.2 Agglomeration. Agglomeration effects in steam power are one prominent reason why adoption may be inefficiently slow, motivating a potential role for policy intervention. We can now use the estimated model to directly assess the quantitative importance of agglomeration effects in allowing us to match the economic impacts of steam power.

In particular, in Appendix Table A.19, we estimate the model while forcing $\alpha_S = 0$ and find that this constrained model can only account for around half of the differential growth we observe in the low-water region.

By contrast, we do not find economically significant agglomeration effects in steam purchase prices. In particular, in Appendix Table A.19, we also estimate the model while forcing $\kappa = 0$, and find that this constrained model still matches the differential steam adoption and economic growth in the low-water region. This suggests that information about steam, such as its existence, costs, and benefits, was not a major barrier to adoption: having more steam-using neighbors did not make mills more likely to adopt, other than through the measured productivity spillover.

D.3.6.3 Forward-Looking Establishment Behavior We model firm behavior with forward-looking expectations. Some mills adopt steam power even though they anticipate that steam adoption costs will continue to fall. Other mills choose to enter using water power, even knowing they will face switching barriers if they later become more productive and then desire to scale up production with steam power.

To illustrate the importance of incorporating forward-looking expectations in the model, we re-estimate the model assuming that establishments are fully myopic ($\delta = 0$). We find that myopia would imply an implausibly low estimate for the startup capital cost of milling. With forward-looking millers, we estimate that the total startup costs, $f_o^E + c(W)$, are 43% of median firm sales. By contrast, we estimate that total startup costs are about 10% of median firm sales if millers are myopic. As a benchmark, the median water mill in 1850 had a capital stock worth 51% of annual sales (which is not a data feature used in the model estimation).

D.4 Additional Counterfactual Details

D.4.1 Distributional Impacts of Steam Adoption: Incumbents vs. Entrants

This section examines how the aggregate gains from steam are distributed between incumbent mills and entrants. We evaluate the impact of steam on milling activity and firm values under different scenarios.

Appendix Table A.20 reports the impact of steam power on milling activity, separately for 1830 incumbents and all future entrants. We focus on incumbents in 1830 because incumbency in later periods is endogenous to the arrival of steam power.

Entrants account for nearly all of the increase in economic activity from steam power in both the baseline region (Column 1) and the region with lower waterpower potential (Column 2). Entrant revenues rise by 144% and 264%, respectively, while incumbent revenues increase by just 0.2% and 0.3%. The small incumbent revenue gains reflect that increased competition from entrants fully offsets the direct benefits of improved technology. Quantitatively, the net effects on 1830 incumbents are small because steam power diffused relatively slowly.

These unequal gains from steam power are consistent with our findings in Section III.B, in which incumbents have lower survival rates in regions with lower waterpower potential where steam is diffusing faster. These counterfactuals report the total impact of steam on milling, including "level effects" shared across regions, whereas the estimates from Section III.B identify only the relative impact of steam power across regions.

Appendix Table A.21 shows the impact of steam power on 1830 incumbents' firm values, decomposed into operating profits, the option value of exit, and the option value of steam (see Appendix D.4.2.1 for formal definitions).[63]

Although Appendix Table A.20 shows that steam modestly raised incumbent revenues, Appendix Table A.21 shows that it did not increase firm values in either of the regions (Columns 1 and 2). This reflects costly adjustments: some incumbents adopted steam and incurred associated overhead and switching costs. Much of the loss in incumbent profits was offset by the option to exit the market. After accounting for profits and exit, the option value of steam recoups 93–98% of the losses in firm value.

Columns 3 and 4 of Appendix Table A.20 explore how switching barriers affect the distributional impact of steam power. When switching is costless (Column 3), steam raises incumbent revenues more than in the baseline; with infinite switching barriers (Column 4), the increase is smaller. Yet, as Appendix Table A.21 shows, effects on total incumbent values remain muted: while the option value of steam is larger without lock-in (1.2% vs. 0%), this is offset by heightened entry and competition, depressing incumbent profits (–3.6% vs. –0.5%).

This result highlights the importance of accounting for forward-looking firm behavior and endogenous competition. Eliminating switching barriers benefits locked-in incumbents, but also spurs entry, ultimately intensifying competition. Quantitatively, the increase in competition offsets the direct benefits to incumbents, leaving them no better off from the arrival of steam.

As a consequence, our model implies that the aggregate gains from steam power accrue primarily to consumers. New entrants raise output and lower prices, while incumbents capture little of the surplus.

D.4.2 Technical Definitions

D.4.2.1 Option Value Decomposition. In this section, we describe how to decompose firm values into operating profits, the option value of exit, and the option value of steam power, as discussed in Section D.4.1.

The value of a water mill is determined by its productivity (its idiosyncratic state variable, φ), the steam adoption cost path (the exogenous aggregate state variable, $\mathbf{c_t^S} = \{c_\tau^S\}_{\tau=t}^{\infty})$,

[63] Because the free entry condition holds, the net surplus generated by entrants is fully passed through to lower consumer prices. Although some productive firms thrive with steam, their gains are offset, on average, by losses among failed entrants.

the paths for the price index and steam adoption rate (the endogenous state variables, $\mathbf{P_t}$ and $\mathbf{s_t}$), its exit cost $\nu^W(1)$, and other time-invariant parameters captured by V:

$$\mathbb{E}_\varepsilon[V^o_{ct}(\varphi, W)] = V(\varphi, \mathbf{c}^{\mathbf{S}}_{\mathbf{Bt}}, \mathbf{P}_{\mathbf{Bt}}, \mathbf{s}_{\mathbf{Bt}}, \nu^W_B(1)), \tag{26}$$

where subscript B denotes the baseline values.

The option value of steam power reflects the difference in firm value when the water mill cannot access steam power, keeping all other state variables fixed at their baseline values:

$$\mathrm{OVS}_t(\varphi, W) = V(\varphi, \mathbf{c}^{\mathbf{S}}_{\mathbf{Bt}}, \mathbf{P}_{\mathbf{Bt}}, \mathbf{s}_{\mathbf{Bt}}, \nu^W_B(1)) - V(\varphi, \infty, \mathbf{P}_{\mathbf{Bt}}, \mathbf{s}_{\mathbf{Bt}}, \nu^W_B(1)) \tag{27}$$

The option value of exit reflects the additional difference in firm value relative to being forced to stay in business indefinitely:

$$\mathrm{OVE}_t(\varphi, W) = V(\varphi_t, \infty, \mathbf{P}_{\mathbf{Bt}}, \mathbf{s}_{\mathbf{Bt}}, \nu^W_B(1)) - V(\varphi_t, \infty, \mathbf{P}_{\mathbf{Bt}}, \mathbf{s}_{\mathbf{Bt}}, \infty) \tag{28}$$

Finally, combining Equations (26)–(28), we can decompose the value of a water mill into operating profits of a water mill that is forced to stay in business, the option value of exit, and the option value of steam power:

$$\mathbb{E}_\varepsilon[V^o_{ct}(\varphi, W)] = V(\varphi_t, \infty, \mathbf{P}_{\mathbf{Bt}}, \mathbf{s}_{\mathbf{Bt}}, \infty) + \mathrm{OVE}_t(\varphi, W) + \mathrm{OVS}_t(\varphi, W). \tag{29}$$

D.4.2.2 Measuring Surplus. This Appendix section defines how we measure surplus in Section V.C, within the flour and lumber sector.

Let subscripts 0 and 1 denote the baseline and policy equilibria, respectively. We consider the welfare effects in year t_0 of a policy that compensates water incumbents by reimbursing a share $\theta > 0$ of the sunk purchase cost $C(W)$ of their water capital if they switch to steam.

We measure aggregate surplus as the sum of incumbent producer surplus (IPS), entrant producer surplus (EPS), and consumer surplus (CS), net of capital expenditures (CE):

$$\mathrm{NetSurplus} = \mathrm{IPS} + \mathrm{EPS} + \mathrm{CS} - \mathrm{CE}. \tag{30}$$

We report these in percentage of baseline aggregate sales in the year of the policy:

$$\mathrm{Sales}_{0t_0} = P_{0t_0} Y_{0t_0}. \tag{31}$$

Capital expenditure. The expenditures from removing sunk water capital are:

$$\text{CE} = \theta C(W) \times \int F_{t_0-1}(W,\varphi)\mathbb{E}_{(\varphi'|\varphi)}\left[O_{1t_0}(W,\varphi')\,\text{Pr}_{1t_0}(S|W,\varphi')\right]\, d\varphi, \tag{32}$$

where $F_{t_0-1}(R,\varphi)$ is the mass of water mills with productivity φ in the year before the policy, $O_{1t_0}(W,\varphi')$ is the probability that a water incumbent with current productivity φ' chooses to operate under the policy, and $\text{Pr}_{1t_0}(S|W,\varphi)$ is its probability of switching to steam. In Section V.C, we calibrate θ such that CE constitutes one percent of Sales_{0t_0}.

Incumbent producer surplus. We measure incumbent surplus as the impact on firm values at the time of enactment:

$$\text{IPS} = \sum_R \int F_{t_0-1}(R,\varphi)\,\left\{\mathbb{E}_{(\varphi'|\varphi)}\left[V_{1t_0}(R,\varphi') - V_{0t_0}(R,\varphi')\right]\right\} d\varphi, \tag{33}$$

where $F_{t_0-1}(R,\varphi)$ is the mass of firms with chosen power R and productivity φ in the year before the policy, and $\mathbb{E}_{(\varphi'|\varphi)}[V_{st_0}(R,\varphi')]$ is their expected continuation values under equilibrium $s \in \{0,1\}$.

Entrant producer surplus. The entrant surplus in year t is given by the change in net values reaped by entrants:

$$\text{EPS}_t = M_{1t}\left\{\mathbb{E}_\varphi[V_{1t}(E,\varphi)] - f^e\right\} - M_{0t}\left\{\mathbb{E}_\varphi[V_{0t}(E,\varphi)] - f^e\right\}, \tag{34}$$

where M_{st} is the mass of entrants under equilibrium $s \in \{0,1\}$, $\mathbb{E}_\varphi[V_{st}(E,\varphi)]$ is the expected entry value, and f^e is the entry cost. Entrant producer surplus is zero under free entry. The total entrant producer surplus of the policy is

$$\text{EPS} = \sum_{t=t_0}^{\infty} \delta^{t-t_0}\text{EPS}_t. \tag{35}$$

Consumer surplus. We measure changes in consumer surplus using equivalent-variation impacts on consumer prices. That is, we calculate the monetary transfer that would deliver the same change in real consumption as that induced by impacts on prices.

As specified in Section IV.A, consumers' utility from mills' products is CES with elasticity ϵ, such that $P_{ct} = \left[\int p_{jct}^{1-\epsilon}\, dj\right]^{\frac{1}{1-\epsilon}}$ is the utility-consistent price index.

The equivalent variation EV_t of the policy is then the additional expenditure that would make consumers in the baseline equilibrium as well off as under the policy equilibrium prices:

$$\frac{C_{0t} + \mathrm{EV}_t}{P_{0t}} = \frac{C_{0t}}{P_{1t}} \iff \mathrm{EV}_t = C_{0t}\left(\frac{P_{0t}}{P_{1t}} - 1\right), \tag{36}$$

where C_{0t} denotes baseline nominal consumption.

The present-discounted consumer surplus from a policy enacted in t_0 is then:

$$\mathrm{CS} = \sum_{t=t_0}^{\infty} \delta^{t-t_0} \mathrm{EV}_t. \tag{37}$$

We measure consumption as total sales net of firm profits and costs:

$$C_t = \mathrm{Sales}_t - \mathrm{FlowProfits}_t - \mathrm{EntryCosts}_t - \mathrm{OperateCosts}_t - \mathrm{PowerCosts}_t, \tag{38}$$

with

$$\mathrm{FlowProfits}_t = \tfrac{1}{\epsilon}\,\mathrm{Sales}_t \tag{39}$$

$$\mathrm{EntryCosts}_t = M_t f^e \tag{40}$$

$$\mathrm{OperateCosts}_t = \mathrm{OpCostEntrants}_t + \mathrm{OpCostsIncumbents}_t \tag{41}$$

$$\mathrm{OpCostEntrants}_t = f_o^E M_t \mathbb{E}_\varphi \left[O_t(E,\varphi)\right] \tag{42}$$

$$\mathrm{OpCostsIncumbents}_t = \sum_R f_o^R \int F_{t-1}(R,\varphi)\mathbb{E}_{(\varphi'|\varphi)}\left[O_t(R,\varphi')\right]\, d\varphi \tag{43}$$

$$\mathrm{PowerCosts}_t = \mathrm{PowCostsEntrants}_t + \mathrm{PowCostsIncumbents}_t \tag{44}$$

$$\mathrm{PowCostsEntrants}_t = M_t \sum_R c_t(E,R)\mathbb{E}_\varphi\left[O_t(E,\varphi)\mathrm{Pr}_t(R|E,\varphi)\right] \tag{45}$$

$$\mathrm{PowCostsIncumbents}_t = \sum_R \int F_{t-1}(R,\varphi)\mathbb{E}_{(\varphi'|\varphi)}\left[O_t(R,\varphi')\right] \sum_{R'} c_t(R,R')\mathrm{Pr}_t(R'|R,\varphi)\, d\varphi, \tag{46}$$

Because impacts are evaluated relative to the baseline consumption path, this formulation yields a conservative (lower-bound) estimate of increases in consumer surplus from reductions in prices.

Appendix References

Abramitzky, Ran, Leah Boustan, Elisa Jácome, and Santiago Pérez. 2021a. "Intergenerational Mobility of Immigrants in the United States over Two Centuries." *American Economic Review*, 111(2): 580–608.

Abramitzky, Ran, Leah Boustan, Katherine Eriksson, James Feigenbaum, and Santiago Pérez. 2021b. "Automated Linking of Historical Data." *Journal of Economic Literature*, 59(3): 865–918.

Adams, Edward Dean. 1927. *Niagara Power: History of the Niagara Falls Power Company, 1886-1918.* Vol. 1, Niagara, NY: The Niagara Falls Power Company.

Allcott, Hunt, Allan Collard-Wexler, and Stephen D. O'Connell. 2016. "How do Electricity Shortages Affect Industry? Evidence from India." *American Economic Review*, 106(3): 587–624.

Allen, Robert C. 2009. *The British Industrial Revolution in Global Perspective.* Cambridge, England: Cambridge University Press.

Andreas, A.T. 1881. *History of Milwaukee, Wisconsin.* The Western Historical Company.

Andrews, Isaiah, Matthew Gentzkow, and Jesse M. Shapiro. 2017. "Measuring the Sensitivity of Parameter Estimates to Estimation Moments." *The Quarterly Journal of Economics*, 132(4): 1553–1592.

Atack, Jeremy, and Fred Bateman. 1999. "Nineteenth-Century US Industrial Development through the Eyes of the Census of Manufactures: A New Resource for Historical Research." *Historical Methods: A Journal of Quantitative and Interdisciplinary History*, 32(4): 177–188.

Atack, Jeremy, Fred Bateman, and Robert A. Margo. 2004. "Skill Intensity and Rising Wage Dispersion in Nineteenth-Century American Manufacturing." *The Journal of Economic History*, 64(1): 172–192.

Bailey, Martha J., Connor Cole, Morgan Henderson, and Catherine Massey. 2020. "How Well do Automated Linking methods perform? Lessons from US Historical Data." *Journal of Economic Literature*, 58(4): 997–1044.

Balke, Neele, and Thibaut Lamadon. 2022. "Productivity Shocks, Long-Term Contracts, and Earnings Dynamics." *American Economic Review*, 112(7): 2139–2177.

Barrows, Frederic Irving. 1917. *History of Fayette County, Indiana: Her People, Industries and Institutions.* Indianapolis, IN: B.F. Bowen.

Bates, Roy M. 1945. *The Water-Powered Mills of Allen County, Indiana.* Self-published.

Bates, Samuel P. 1884. *History of Erie County, Pennsylvania.* Chicago: Warner, Beers & Co.

Berger, David, and Joseph Vavra. 2015. "Consumption Dynamics during Recessions." *Econometrica*, 83(1): 101–154.

Bleakley, Hoyt, and Jeffrey Lin. 2012. "Portage and Path Dependence." *The Quarterly Journal of Economics*, 127(2): 587–644.

Bureau, United States Census. 1919. *Statistical Abstract of the United States.* U.S. Government Printing Office. Accessed via FRASER, Federal Reserve Bank of St. Louis.

Campbell, Marius R. 1908. "Coal Fields of the United States." *United States Geological Survey, Washington, D.C.*

Charlier, Roger H., and Loïc Menanteau. 1997. "The Saga of Tide Mills." *Renewable and Sustainable Energy Reviews*, 1(3): 171–207.

Chen, Tianqi, and Carlos Guestrin. 2016. "XGBoost: A Scalable Tree Boosting System." 785–794.

Cole, Arthur H. 1938. *Wholesale Commodity Prices in the United States, 1700-1861.* Cambridge, MA: Harvard University Press.

Delle Donne, Carmen. 1973. *Federal Census Schedules, 1850-1880: Primary Sources for Histor-*

ical Research. Washington, DC: National Archives and Records Service.

Donaldson, Dave, and Richard Hornbeck. 2016. "Railroads and American Economic Growth: A "Market Access" Approach." *The Quarterly Journal of Economics*, 131(2): 799–858.

Dondlinger, Peter Tracy. 1919. *The Book of Wheat: An Economic History and Practical Manual of the Wheat Industry.* New York: Orange Judd Company.

Ellis, Franklin, and Austin N Hungerford. 1886. *History of That Part of the Susquehanna and Juniata Valleys: Embraced in the Counties of Mifflin, Juniata, Perry, Union and Snyder, in the Commonwealth of Pennsylvania.* Vol. 1, Philadelphia: Everts, Peck & Richards.

Emery, Charles E. 1883. "The Cost of Steam Power." *Transactions of the American Society of Civil Engineers*, 12(1): 425–431.

Feigenbaum, James. 2015. "Automated Census Record Linking: A Machine Learning Approach." Working Paper.

Feigenbaum, James, James Lee, and Filippo Mezzanotti. 2022. "Capital Destruction and Economic Growth: The Effects of Sherman's March, 1850–1920." *American Economic Journal: Applied Economics*, 14(4): 301–342.

Fellegi, Ivan P, and David Holt. 1976. "A Systematic Approach to Automatic Edit and Imputation." *Journal of the American Statistical Association*, 71(353): 17–35.

Fenneman, Nevin M. 1946. "Physical Divisions of the United States." US Geological Survey Report.

Ferrie, Joseph P. 1996. "A New Sample of Males Linked from the Public Use Microdata Sample of the 1850 US Federal Census of Population to the 1860 US Federal Census Manuscript Schedules." *Historical Methods: A Journal of Quantitative and Interdisciplinary History*, 29(4): 141–156.

Flour and Feed. 1945. *Devoted to the Interests of the Flour and Feed Trade.* Vol. 22, Milwaukee, Wisconsin.

Fogel, Robert W. 1964. *Railroads and American Economic Growth: Essays in Econometric History.* Baltimore: Johns Hopkins University Press.

G.W. & C.B. Colton & Co. 1882. "Colton's Railroad Map (Intermediate Size) of the United States."

Haines, Michael R. 2010. "Historical, Demographic, Economic, and Social Data: The United States, 1790–2002." *ICPSR Volume 2896.*

Hanlon, W. Walker. 2022. "The Rise of the Engineer: Inventing the Professional Inventor during the Industrial Revolution." Working Paper.

Hardesty, Roger David. 2019. "Wild Confusion in Every Direction." *Hard Honesty.*

Hornbeck, Richard. 2010. "Barbed Wire: Property Rights and Agricultural Development." *The Quarterly Journal of Economics*, 125(2): 767–810.

Hornbeck, Richard, and Martin Rotemberg. 2024. "Growth Off the Rails: Aggregate Productivity Growth in Distorted Economies." *Journal of Political Economy*, 132(11): 3547–3602.

Hubbard, Wales. 1861. *Maine Reports: Cases in Law and Equity Determined by the Supreme Judicial Court of Maine.* Vol. XLVI, Hallowell: Masters, Smith & Co.

International Publishing Co. 1887. *Quarter-Century's Progress of New Jersey's Leading Manufacturing Centres: Dover.* New York.

Jackson, Donald C. 1975. "Historic American Engineering Record: Luckenbach Flour Mill." National Park Service.

Jaremski, Matthew. 2014. "National Banking's Role in US Industrialization, 1850–1900." *The Journal of Economic History*, 74(1): 109–140.

Jones, James Edwin. 1914. *A History of Columbia County, Wisconsin: A Narrative Account of Its Historical Progress, Its People, and Its Principal Interests.* Vol. 2, Lewis Publishing Company.

Keane, Michael P., Petra E. Todd, and Kenneth I. Wolpin. 2011. "The Structural Estimation of Behavioral Models: Discrete Choice Dynamic Programming Methods and Applications." In *Handbook of Labor Economics*. Vol. 4, 331–461. Amsterdam: Elsevier.

Kim, Hang, Martin Rotemberg, and T. Kirk White. 2021. "Plant-to-Table (s and figures): Processed Manufacturing Data and Measured Misallocation." *Working Paper.*

McKay, L., T. Bondelid, T. Dewald, J. Johnston, R. Moore, and A. Rea. 2012. "User's Guide for the National Hydrography Dataset Plus Version 2 (NHDPlusV2)." US Environmental Protection Agency Office of Water.

Moore, Richard B., Lucinda D. McKay, Alan H. Rea, Timothy R. Bondelid, Curtis V. Price, Thomas G. Dewald, and Craig M. Johnston. 2019. "User's Guide for the National Hydrography Dataset Plus (NHDPlus) High Resolution." US Geological Survey Open-File Report 2019-1096.

NOAA. 2016. "National Water Model: Improving NOAA's Water Prediction Services." National Oceanic and Atmospheric Administration.

Nurkse, Ragnar. 1953. *Problems of Capital Formation in Underdeveloped Countries.* Oxford: Basil Blackwell.

Ottonello, Pablo, and Thomas Winberry. 2020. "Financial Heterogeneity and the Investment Channel of Monetary Policy." *Econometrica*, 88(6): 2473–2502.

Rothschild, Elaine W. 1976. *A History of Cheltenham Township.* Cheltenham Township Historical Commission.

Ruggles, Steven, Catherine A. Fitch, and Evan Roberts. 2018. "Historical Census Record Linkage." *Annual Review of Sociology*, 44: 19–37.

Rusanov, Vasily. 2021. "Internal Migration and the Diffusion of Schooling in the US." Working Paper.

Scharf, J. Thomas. 1874. *The Chronicles of Baltimore : Being a Complete History of "Baltimore Town" and Baltimore City from the Earliest Period to the Present Time.* Baltimore: Turnbull Bros.

Semple, Ellen Churchill. 1903. *American History and Its Geographic Conditions.* Boston; New York: Houghton, Mifflin.

Sharrer, G. Terry. 1982. "The Merchant-Millers: Baltimore's Flour Milling Industry, 1783-1860." *Agricultural History*, 56(1): 138–150.

Thompson, Katherine Jenny, and Richard S. Sigman. 1999. "Statistical Methods for Developing Ratio Edit Tolerances for Economic Data." *Journal of Official Statistics*, 15(4): 517.

Train, Kenneth E. 2009. *Discrete Choice Methods with Simulation.* Cambridge, England: Cambridge University Press.

United States Census Office. 1850. "Manufacturers of the United States in 1850." *U.S. Department of the Interior.*

United States Census Office. 1860*a*. "Instructions to U.S. Marshals. Instructions to Assistants." U.S. Department of the Interior.

United States Census Office. 1860*b*. "Manufacturers of the United States in 1860." *U.S. Department of the Interior.*

United States Census Office. 1870*a*. "Manufacturers of the United States in 1860." *U.S. Department of the Interior.*

United States Census Office. 1870*b*. "Ninth Census of the United States, 1870: Statistics of the wealth and industry of the United States." U.S. Department of the Interior.

United States Census Office. 1880. "Manufacturers of the United States in 1860." *U.S. Department of the Interior.*

United States Census Office. 1883. "Tenth Census. Volumes 16 & 17. Reports on the Water Power of the United States." *U.S. Department of the Interior*.

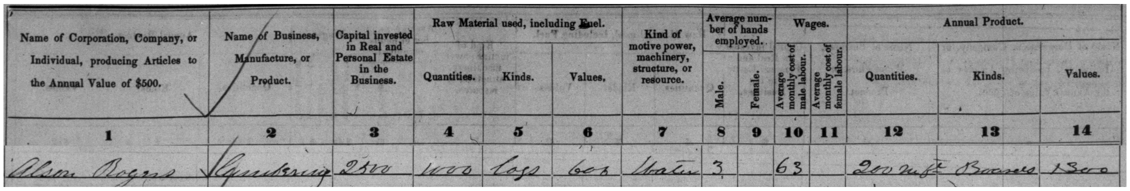
Watertown Historical Society. 2022. "The Yellow Mill (same as the Blanchard Mill)."

Wright, Marvin N, and Andreas Ziegler. 2015. "Ranger: A Fast Implementation of Random Forests for High Dimensional Data in C++ and R." *arXiv preprint arXiv:1508.04409*.

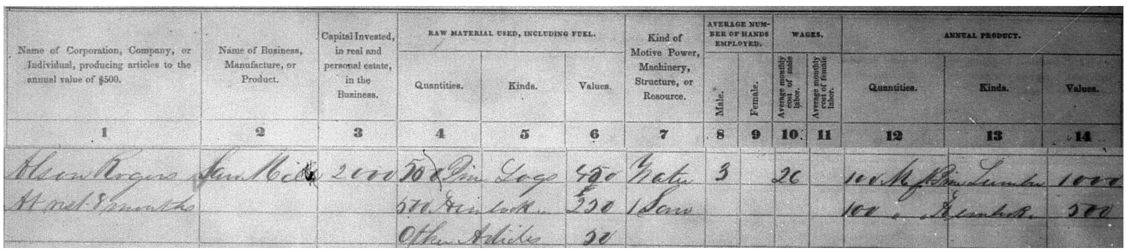
York Township Historical Society. 2023. "The Early History of York Township." York Township Historical Society.

Figure A.1. Example Census Images: The Rogers' Lumber Mill

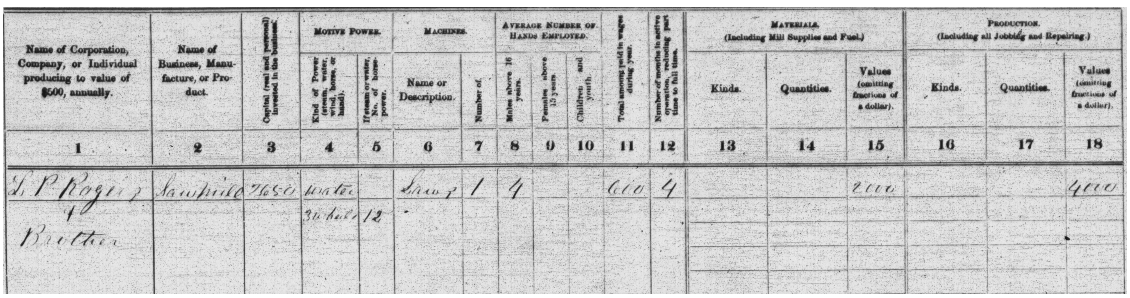
Panel A. 1850



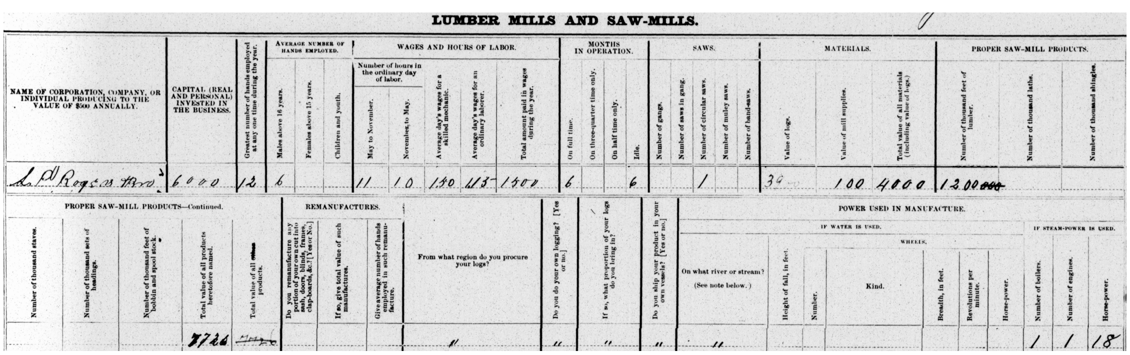
Panel B. 1860



Panel C. 1870

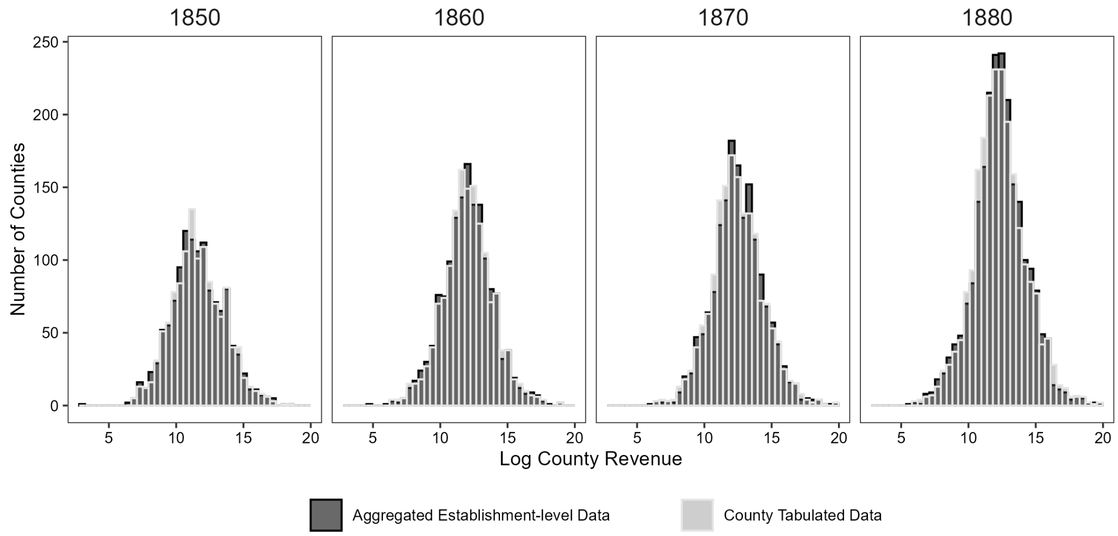


Panel D. 1880



Notes: This figure shows example images for the Census of Manufactures in each decade, and follows the Rogers' Mill across each decade. Alson Rogers settled in Warren, Pennsylvania and started in the lumber business after marrying in 1835. After he passed away in 1867, his sons Lucian (the "L.P." seen in the 1870 and 1880 Census images) and Burton took over the business, and built a steam engine. Sources: Schenck and Rann (1887), Census of Manufacturers (1850-1880), Census of Population (1850-1880).

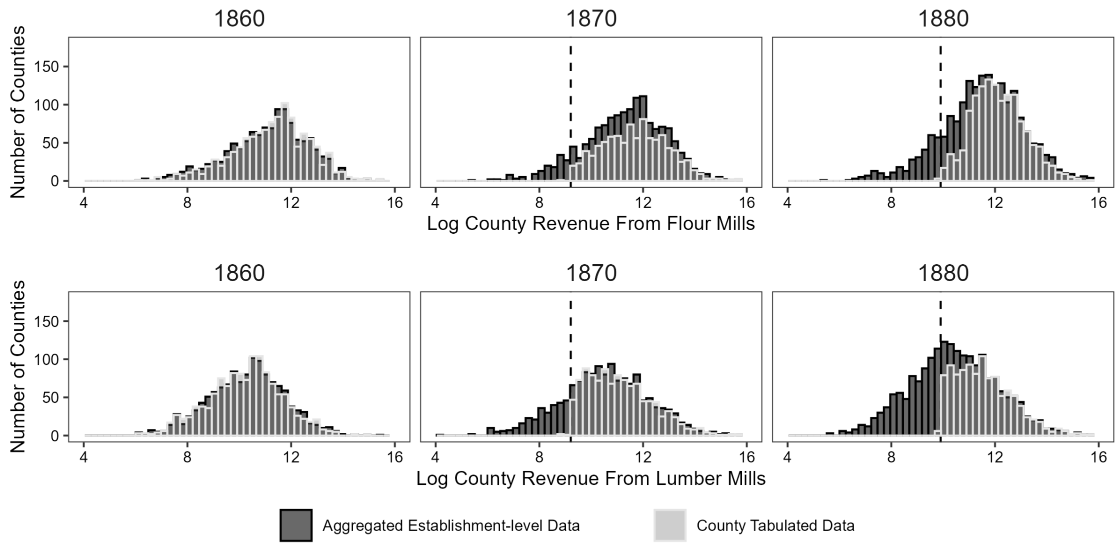
Figure A.2. Distribution of County-Level Manufacturing Revenue, in County-Level Tabulations and Aggregating Our Establishment-Level Data



Notes: This figure shows the distribution of total recorded manufacturing revenue by county, comparing county-level tabulations made contemporaneously by the Census against the county-level sums of our digitized establishment-level data from Census manuscripts. Data from our main sample (Figure 5), using our digitized establishment-level Census of Manufactures (1850-1880), county-level tabulations (Haines, 2010).

Figure A.3. Unreported Data in County-Industry Tabulations, for Flour Mills and Lumber Mills, Compared to Aggregated Establishment-Level Data

Panel A. Distribution of County Revenue for Flour Mills and Lumber Mills, in County-Industry Tabulations or Aggregated Establishment-Level Data

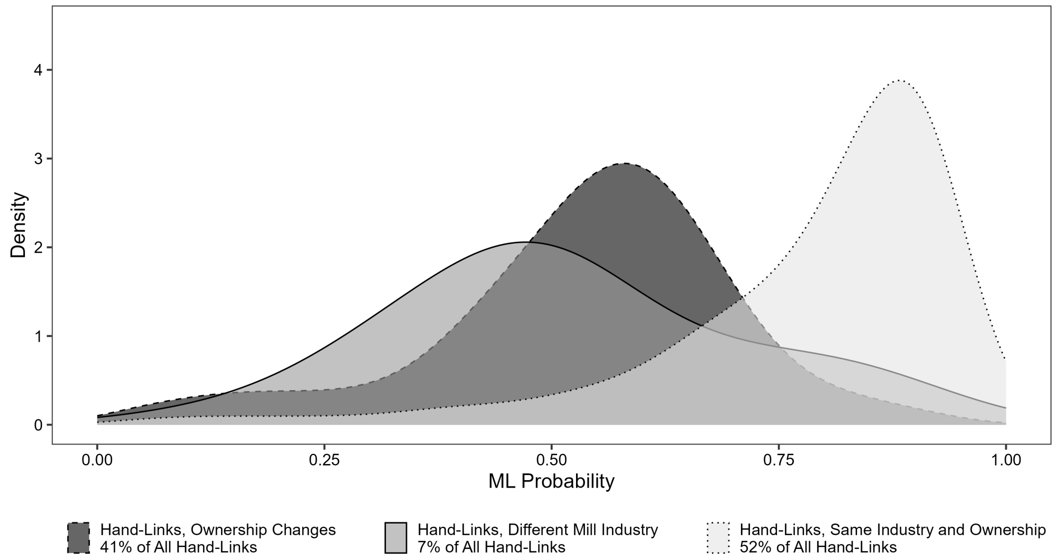


Panel B. Restricted to the Same Counties: Distribution of County Revenue for Flour Mills and Lumber Mills, by Data Source

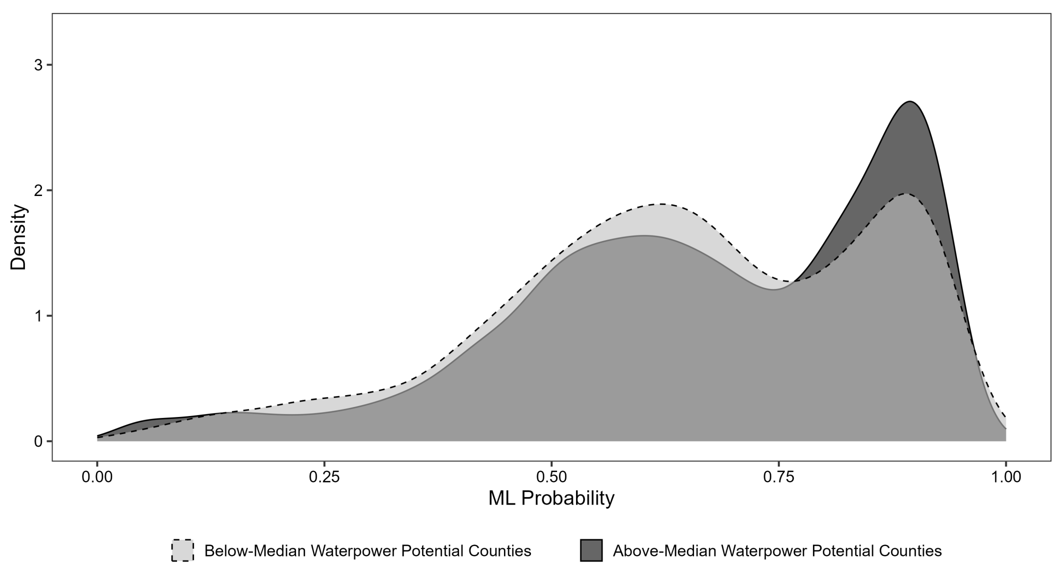
Notes: This figure shows the distribution of total flour mill revenue and total lumber mill revenue, by county, comparing county-industry tabulations for 1860-1880 made contemporaneously by the Census against the county-industry-level sums of our digitized establishment-level data from Census manuscripts (the Census did not publish county by industry tabulations in 1850). Panel A reports the distribution of values for county-industries with data in either source. Panel B reports the distribution of values for only those county-industries for which we have data from both sources. The Census had a *de jure* minimum value of total revenue for reporting county-industry values in 1870 and 1880, which corresponds to the vertical lines, and the Census also omitted tabulations for some other county-industry cells. Data from our main sample (Figure 5), using our digitized establishment-level Census of Manufactures (1860-1880) and county-industry-level tabulations digitized by Hornbeck and Rotemberg (2024).

Figure A.4. Distribution of Hand-Links' ML-Model Probability, by Type and Waterpower Potential

Panel A. Distribution of Hand-Links' ML-Model Probability, by Hand-Link Type



Panel B. Distribution of Hand-Links' ML-Model Probability, by County Waterpower Potential



Notes: Panel A shows the distribution of hand-links by machine-learning probability, separately by the type of hand-link: those in the same industry and same ownership structure; those in a different mill industry (i.e., switched from flour to lumber milling); and those with ownership changes (i.e., added/removed some owners or changes to first names/initials). Panel B shows the distribution of machine-learning probabilities assigned to hand-links, separately for counties with above-median waterpower potential and below-median waterpower potential. The ML-Linking model is described in Appendix A.2.1. Data from our main sample (Figure 5), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

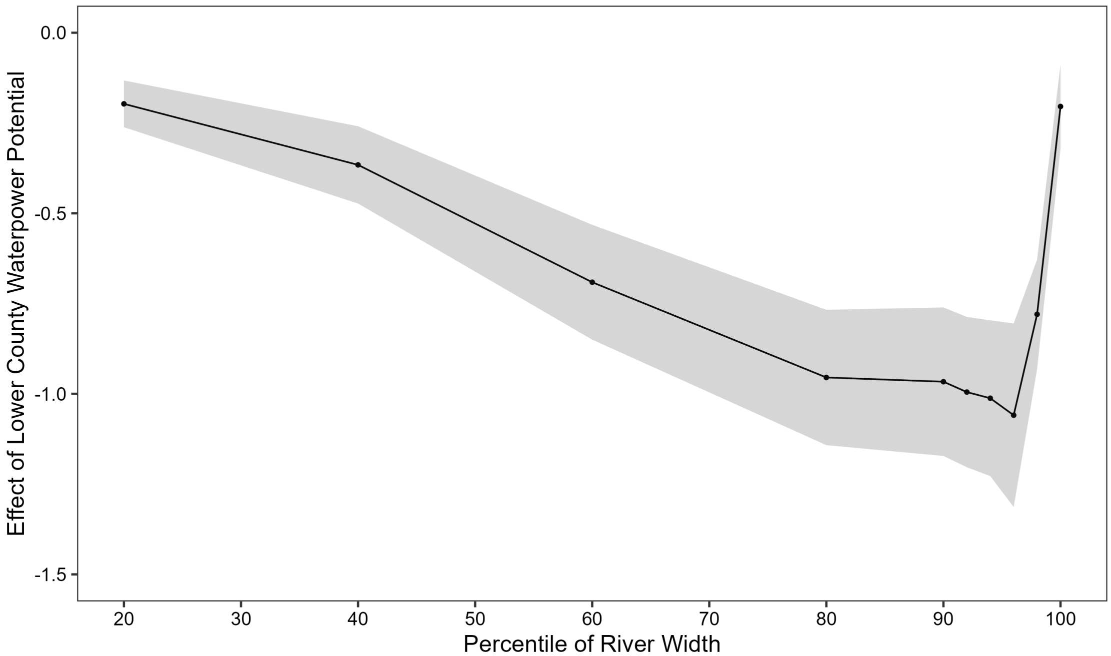
Figure A.5. Components of County Waterpower Potential

Panel A. Flow Rate of River Segments

Panel B. Fall Height of River Segments

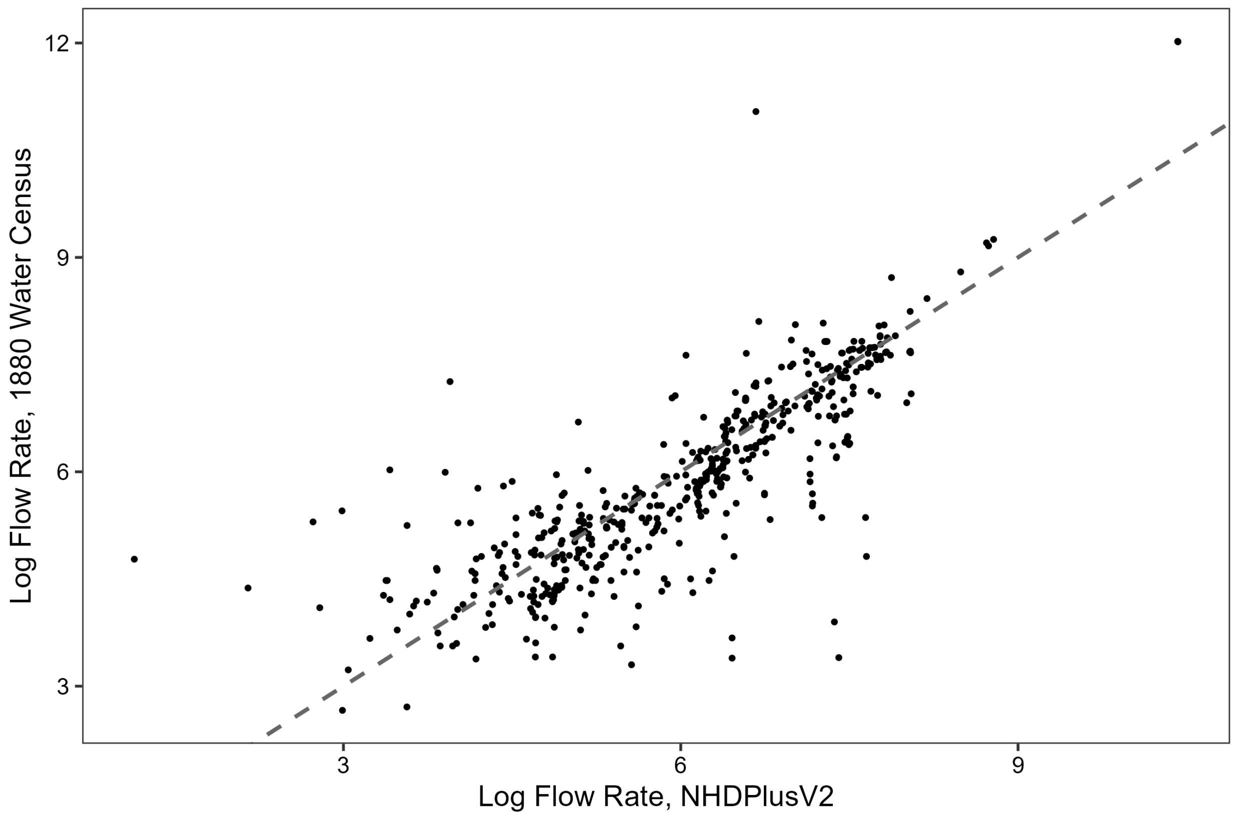
Notes: This figure plots the sources of waterpower potential in the United States, with darker shares corresponding to greater flow rates or fall heights. Panel A plots our estimated flow rates for each river segment, in cubic feet per second. Panel B plots the drop in elevation for each river segment, in feet per mile. Data from NHDPlusV2.

Figure A.6. Estimated Relationship between Water Powered Mills in 1850 and County Waterpower Potential, Excluding Rivers with Widths Above Different Cutoffs



Notes: This figure shows the estimated relationship between a county's number of water powered mills in 1850 and a one standard deviation decrease in county waterpower potential, where county waterpower potential is measured excluding rivers that are wider than the indicated cutoff percentile of river widths. We sort rivers into percentile bins, based on their width, estimate our main specification from Panel A of Table 3, and plot the estimated coefficient on Lower Water power along with its 95% confidence interval. All regressions include our baseline controls interacted with industry: an indicator for the presence of navigable waterways in the county, distance to the nearest navigable waterway, county market access in 1850, an indicator for workable coal deposits in the county, the share of the county covered by coal deposits, and access to coal via the transportation network. Robust standard errors are clustered by county. Data from our main sample (Figure 5), using our digitized establishment-level Census of Manufactures (1850) and NHDPlusV2.

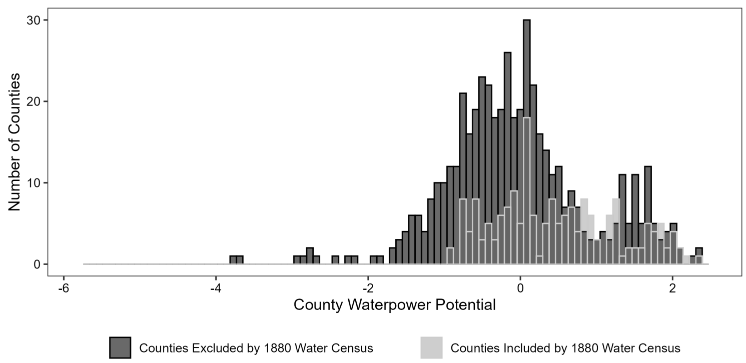
Figure A.7. River Segment Flow Rates, in the 1880 Water Census Compared to NHDPlusV2



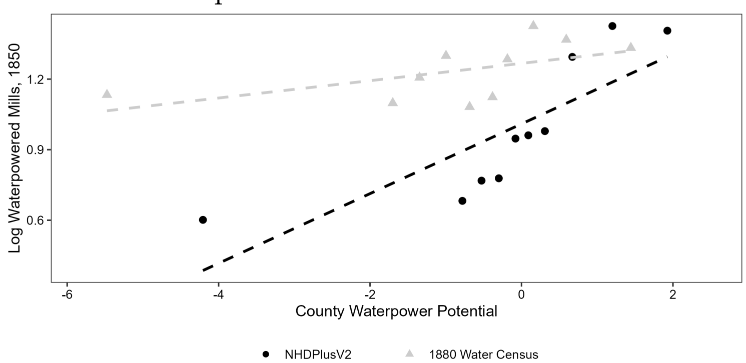
Notes: This figure compares the log water flow rates of river segments that we linked by name from the 1880 Water Census to the National Hydrography Dataset Plus Version 2.0 (NHDPlusV2). Each point represents one linked river segment.

Figure A.8. Selected Coverage in the 1880 Water Census, Compared to Comprehensive NHDPlusV2 Data

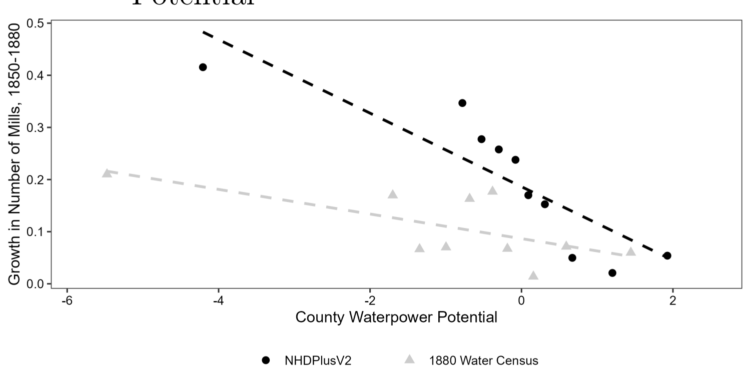
Panel A. Distribution of County Waterpower Potential, for Counties Included and Excluded by 1880 Water Census



Panel B. Measured Relationship between 1850 Water Powered Mills and County Waterpower Potential



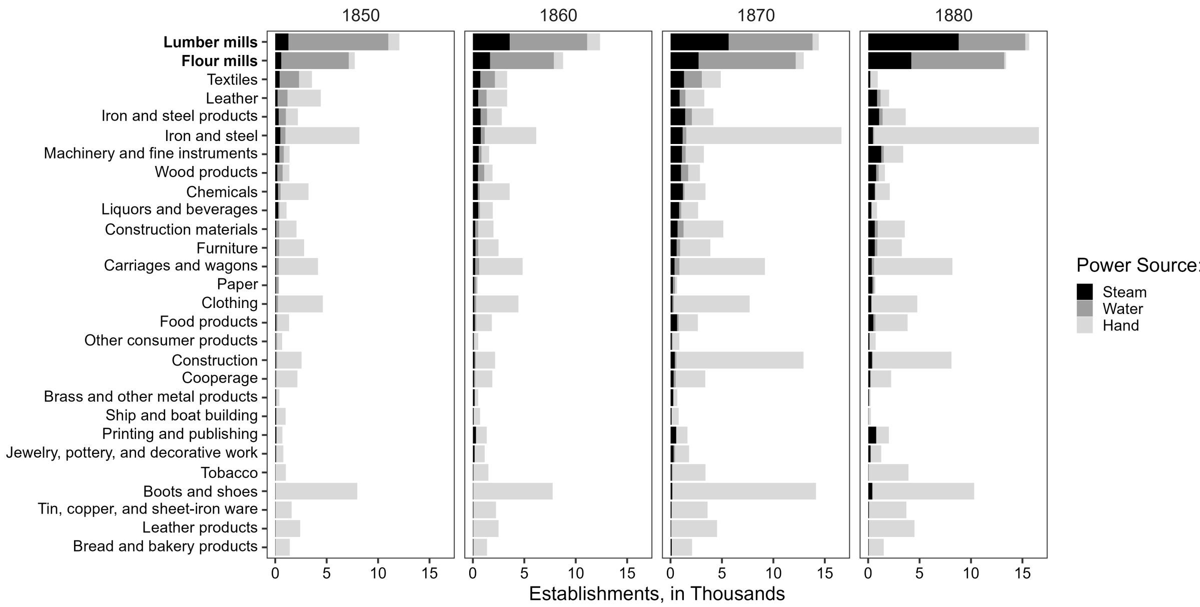
Panel C. Measured Relationship Between 1850–1880 Mill Growth and County Waterpower Potential



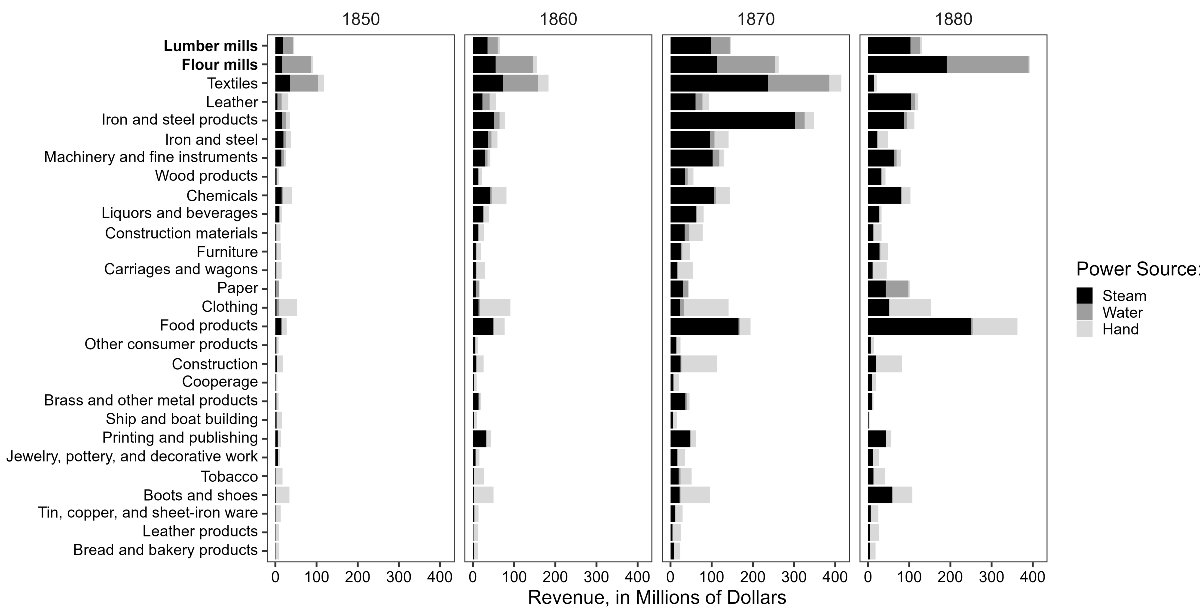
Notes: Panel A shows the distribution of county waterpower potential, measured using NHDPlusV2 data, for counties included by the 1880 Water Census (light gray) and counties excluded by the 1880 Water Census (dark gray). Panel B shows a binscatter of the unadjusted relationship between the number of water powered mills in 1850 and county waterpower potential, using the full NHDPlusV2 data and the Water Census data. Panel C shows a binscatter of the unadjusted relationship between the growth in the number of mills between 1850 and 1880 and county waterpower potential, using the full NHDPlusV2 data and the Water Census data. Panels B and C use PPML estimation, which approximates percent differences in the rates. Data from our main sample (Figure 5), using our digitized establishment-level Census of Manufactures (1850-1880), NHDPlusV2, and United States Census Office (1883).

Figure A.9. Power Source By Industry

Panel A. Number of Establishments, by Power Source

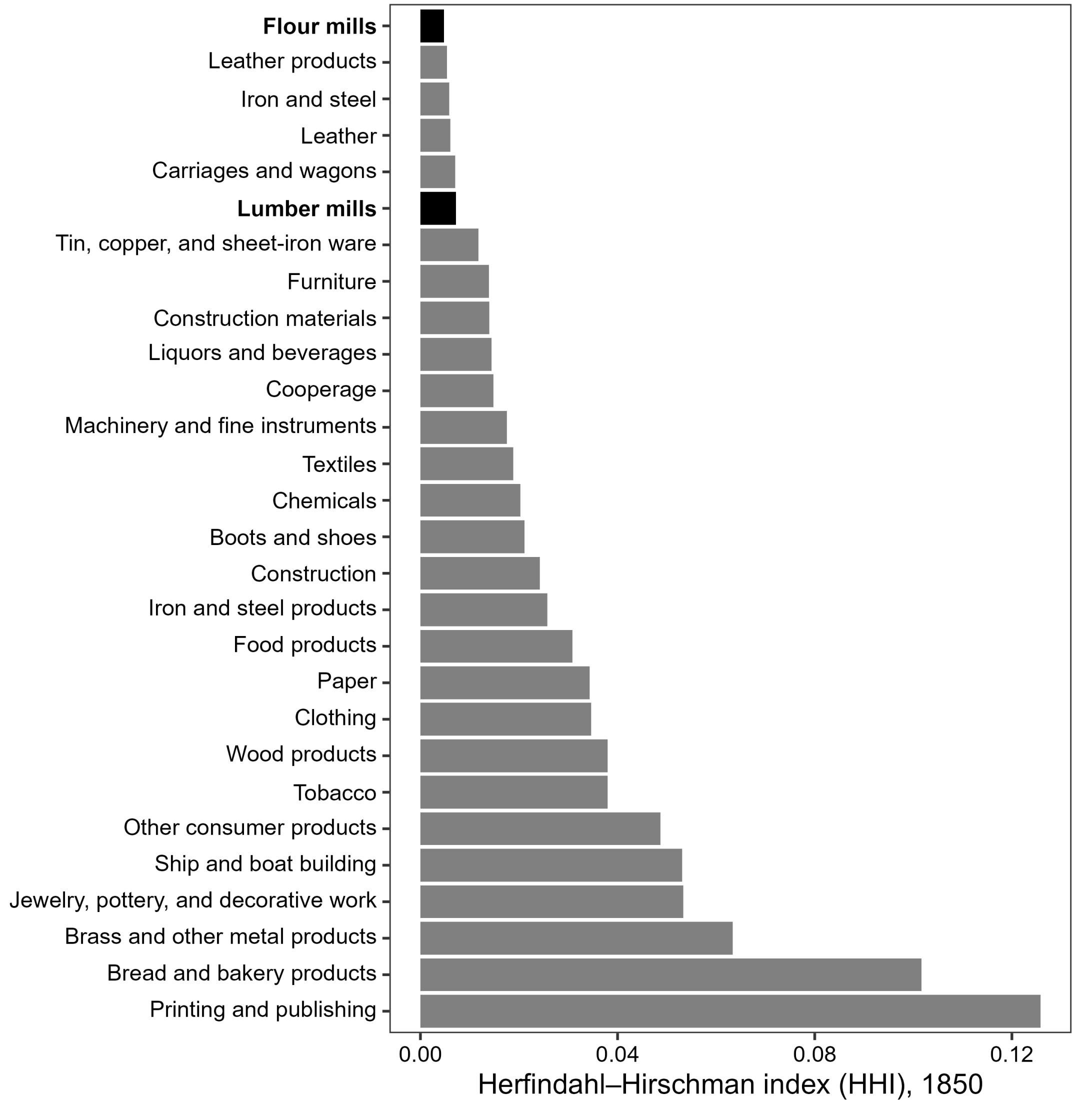


Panel B. Total Revenue, by Power Source



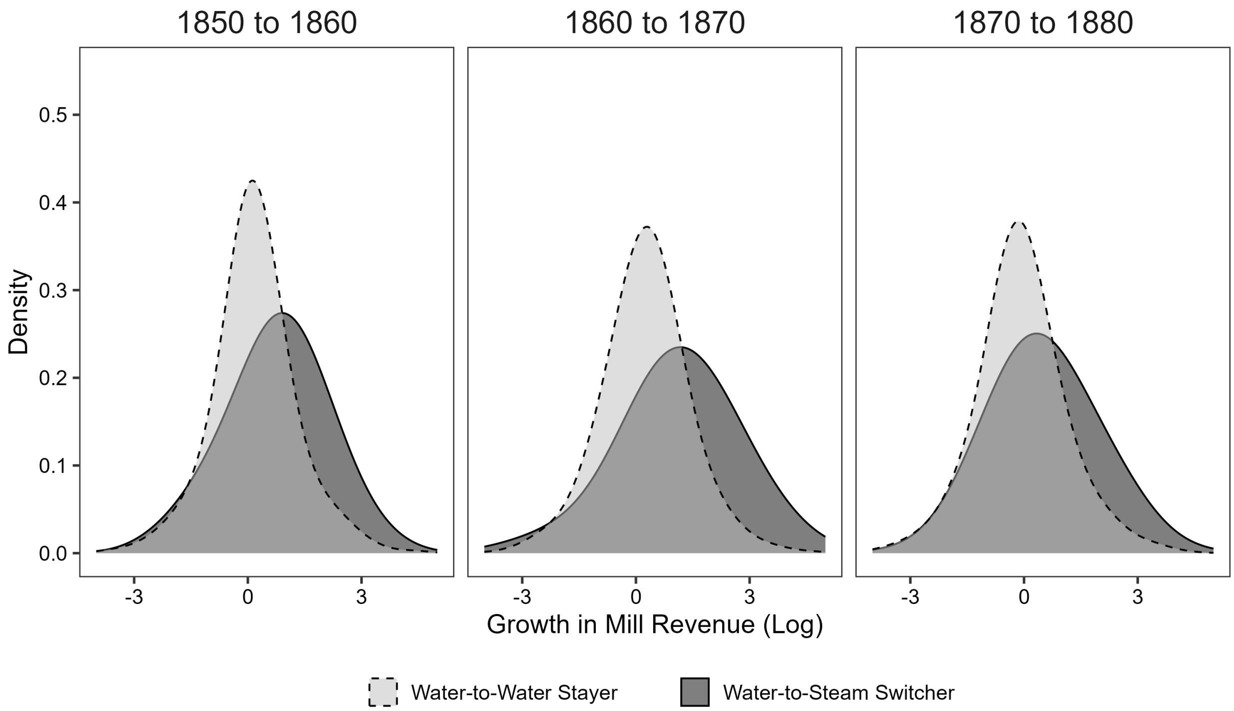
Notes: This figure plots power use, by industry and decade. Industries are sorted by the number of establishments using either steam or water power in 1850 (in decreasing order). Panel A shows the number of establishments in each industry using steam, water, and hand power. Panel B shows the total revenue produced in establishments using steam, water, and hand power. We define "steam" to include all establishments using any steam power; "water" includes establishments using water power and no steam power; "hand" includes the remaining establishments that use neither steam nor water. Data from our digitized establishment-level Census of Manufactures (1850-1880).

Figure A.10. Geographic Concentration of Production in 1850, by Industry



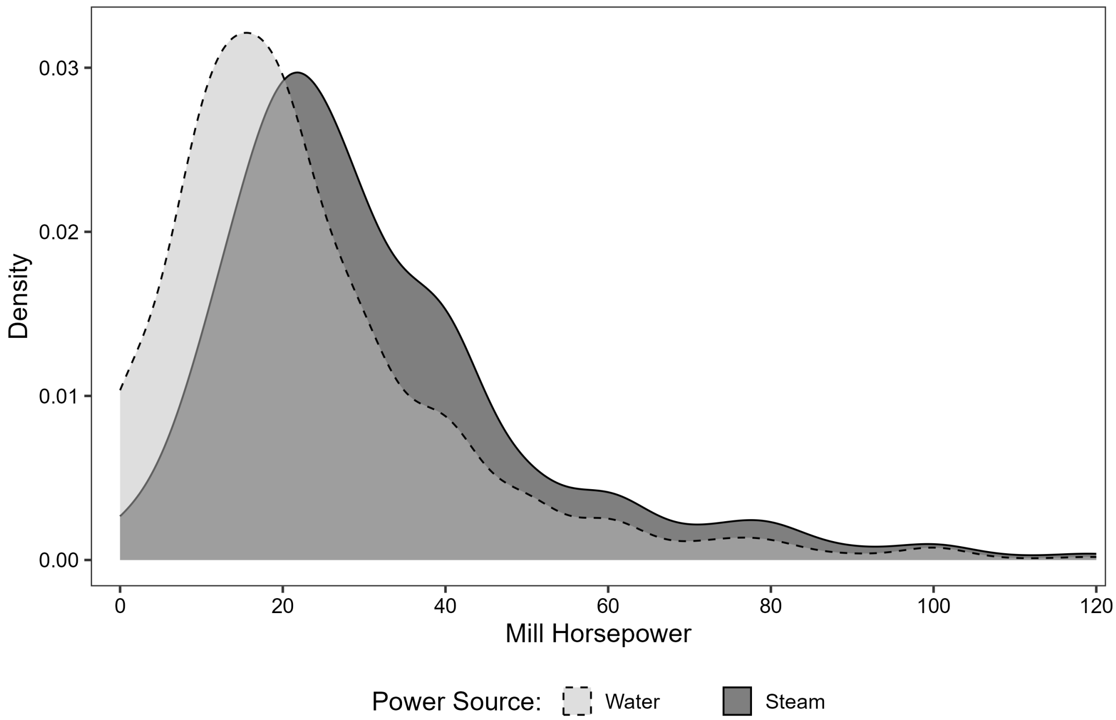
Notes: For each sector, this figure shows the Herfindahl–Hirschman index of revenue across counties in 1850 (sorted in increasing order). Data restricted to counties in our main sample (Figure 5), using our digitized establishment-level Census of Manufactures (1850).

Figure A.11. Growth in Mill Revenue, by Steam Switching Choice



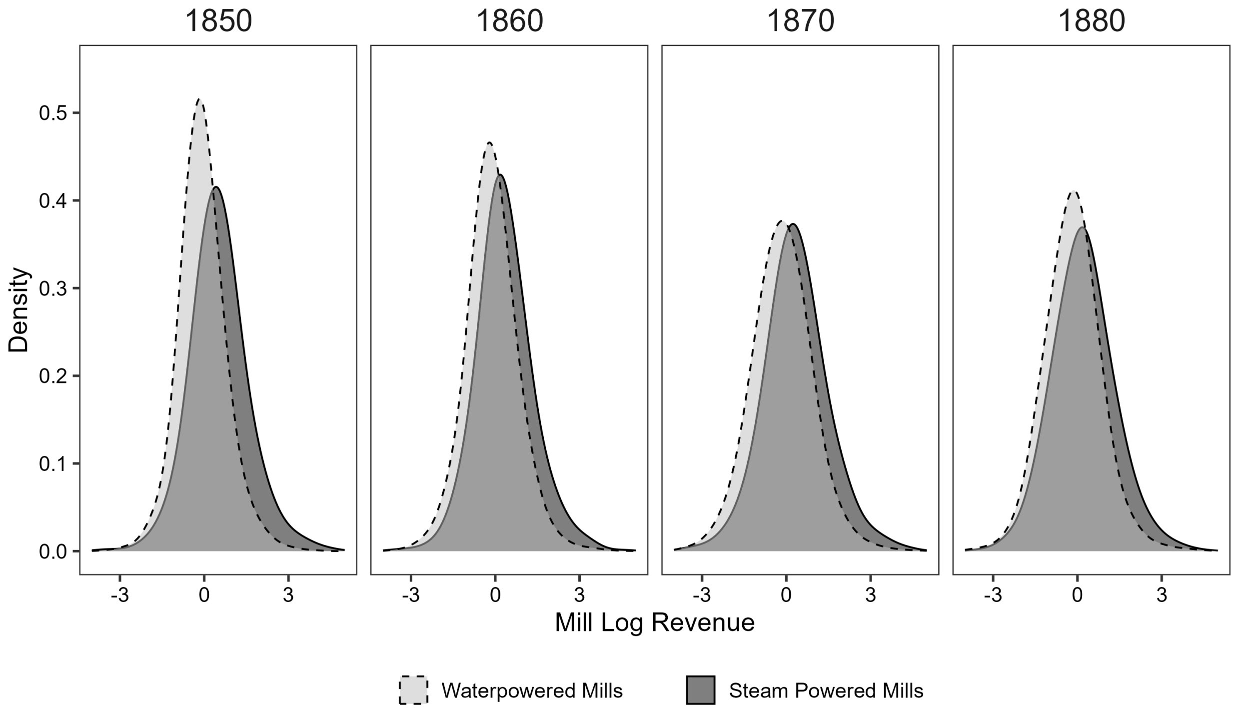
Notes: This figure shows the growth in mill revenue, by decade, for water incumbents who (1) kept using water power or (2) switched from water to steam power. Data from our main sample (Figure 5), using our digitized establishment-level Census of Manufactures (1850-1880).

Figure A.12. Distribution of Total Horsepower Installed, by Power Source



Notes: This figure shows the distribution of horsepower installed for flour mills and lumber mills in 1870 and 1880, pooled across both industries and decades. For this figure, we truncated the data at 120 horsepower. Data from our main sample counties (Figure 5), using our digitized establishment-level Census of Manufactures (1870 and 1880).

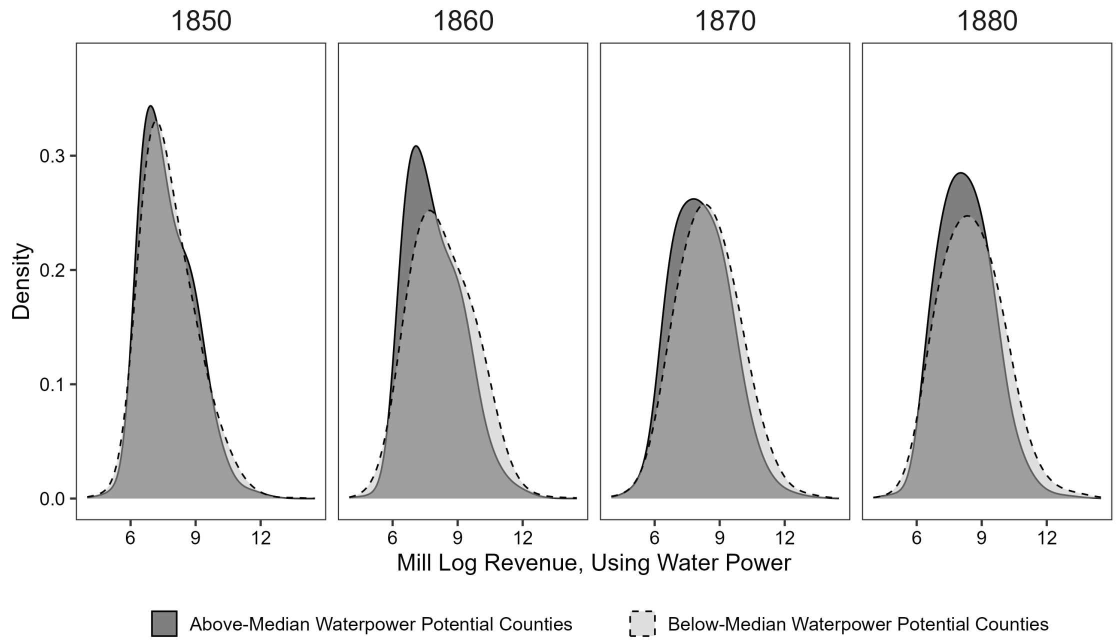
Figure A.13. Mill Size by Power Source, Within-County



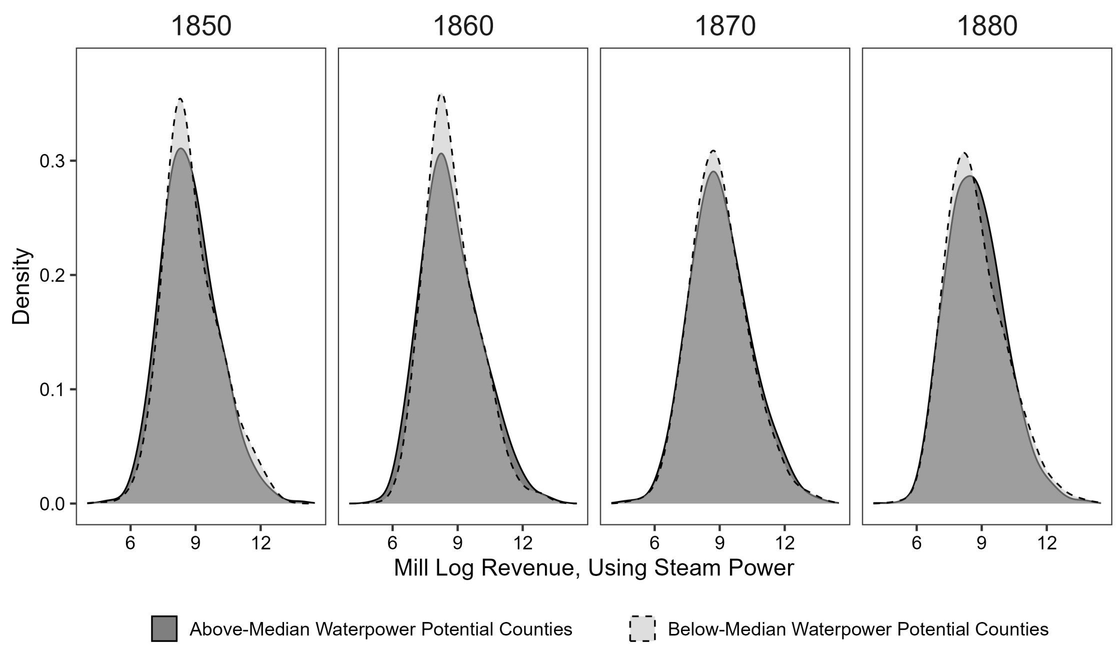
Notes: This figure shows the distribution of mill revenue, in each decade, for each type of power source (steam or water). For each mill, we subtract mean log revenue in their county-industry (flour or lumber). Data from our main sample (Figure 5), using our digitized establishment-level Census of Manufactures (1850-1880).

Figure A.14. Mill Size Distribution, by County Waterpower Potential

Panel A. Revenue Distribution of Water-Using Mills

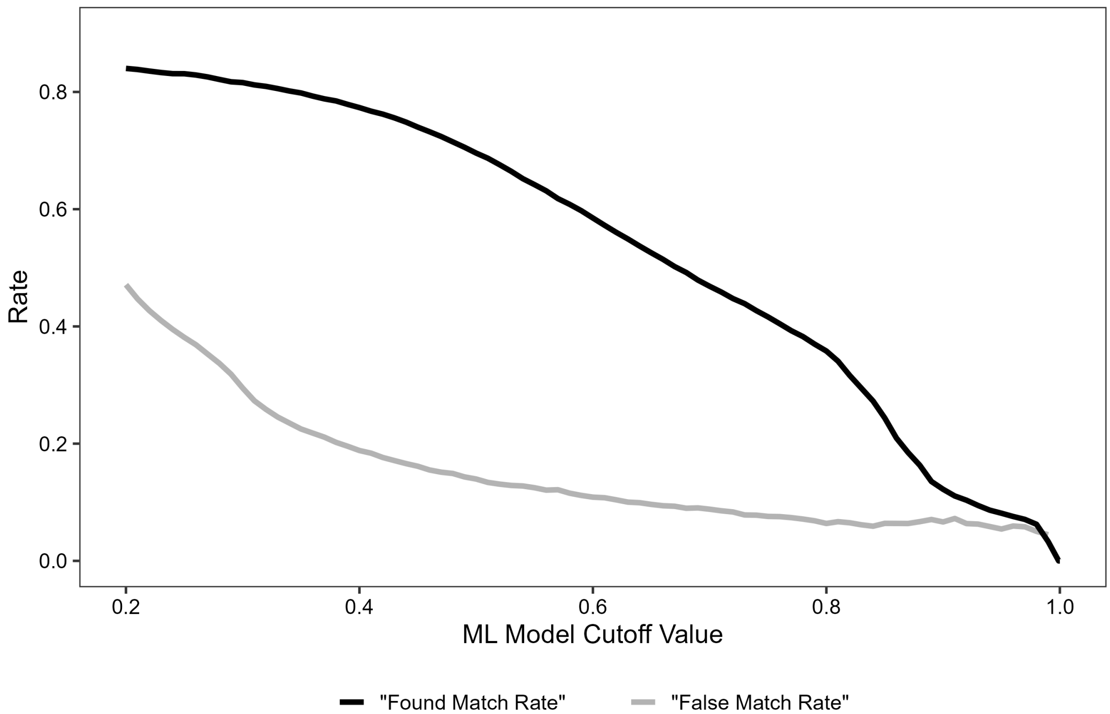


Panel B. Revenue Distribution of Steam-Using Mills



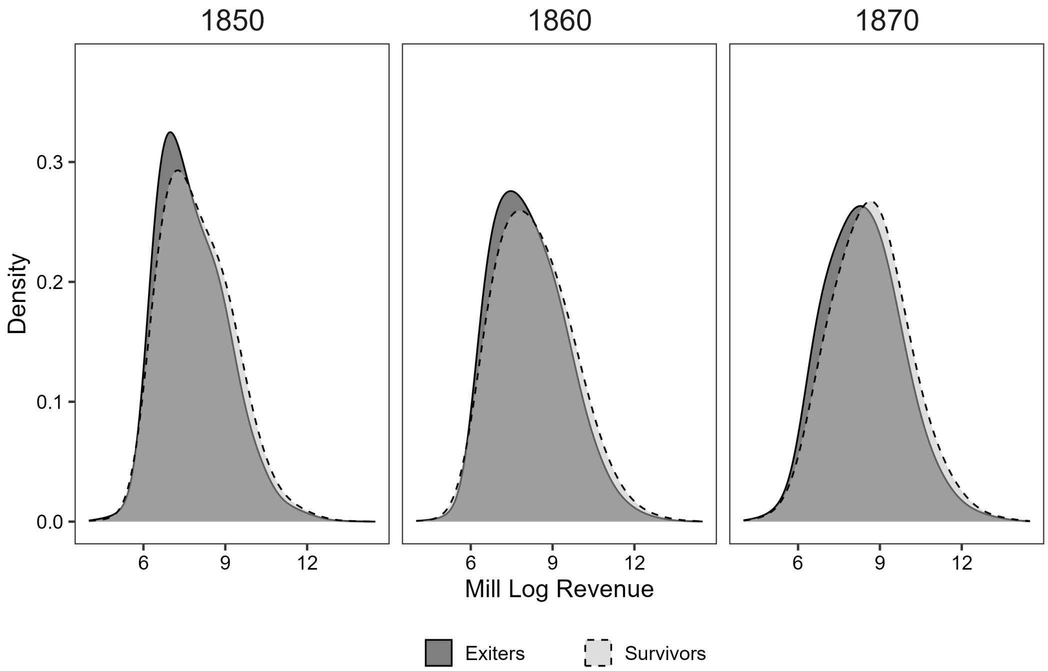
Notes: This figure shows the distribution of mill revenue in each decade, separately for counties with above-median and below-median waterpower potential. Data from our main sample (Figure 5), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Figure A.15. "False Match Rate" and "Found Match Rate" of Machine-Learning Model, Compared to Hand-Links, by Chosen ML-Model Cutoff Value



Notes: For different cutoff values on the machine-learning model predictions, the light gray line shows the share of links made by the machine-learning model that are not hand-links ("False Match Rate," if hand-links are assumed correct). The black line shows the share of hand-links made by the machine-learning model ("Found Match Rate"). The ML model reports a probability that mills in adjacent decades are the same, and the chosen ML-model cutoff value is the lowest probability that we would classify as a match. If there are multiple mills above the cutoff, we match only the highest probability mill. The ML-Linking model is described in Appendix A.2.1. Data are for all lumber and flour mills in our digitized establishment-level Census of Manufactures (1850-1880).

Figure A.16. Initial Mill Size, for Exiters and Survivors



Notes: This figure shows the distribution of mill revenue in each baseline decade, separately for "Exiters" who close in the subsequent decade and "Survivors" who remain in operation by the next Census. Data from our main sample (Figure 5), using our digitized establishment-level Census of Manufactures (1850-1880).

Table A.1. Model Fit to Target Moments

Parameter	Moment	Years	Model	Data
Panel A. Baseline County				
$c(W,S)$	Water Choice Differential:	1850–1880	0.529	0.529
	Water Incumbents vs. Entrants			(0.061)
$c(S,W)$	Steam Choice Differential:	1850–1880	1.019	1.020
	Steam Incumbents vs. Entrants			(0.132)
$c_S^{(initial)}$	Steam Adoption Rate	1850	0.103	0.103
				(0.006)
$c_S^{(terminal)}$	Steam Adoption Rate	1880	0.396	0.396
				(0.011)
f_e	Entry Rate	1850–1860	0.741	0.750
				(0.006)
f_o^E	Log Sales Differential:	1850–1880	0.129	0.129
	Incumbents vs. Entrants			(0.015)
f_o^W	Water Exit Rate	1850–1880	0.791	0.791
				(0.003)
f_o^S	Steam Exit Rate	1850–1880	0.836	0.835
				(0.006)
γ	Log Sales Differential:	1850–1880	0.835	0.836
	Steam vs. Water Users			(0.030)
π	Log Sales Autocorrelation	1850–1860	0.409	0.410
				(0.019)
σ	Log Sales Standard Deviation	1850–1860	1.020	1.020
				(0.011)
Panel B. Differences in Lower Waterpower Counties				
$c_L(W)$	Steam Adoption Rate	1850	0.087	0.087
				(0.016)
η	Log Total Output	1850	-0.880	-0.881
				(0.215)
κ	Change in Steam Adoption Rate	1850, 1880	0.090	0.090
				(0.019)
α	Growth of Output	1850, 1880	0.554	0.554
				(0.114)

Notes: This table shows the empirical fit of our estimated model. The table shows each parameter of the model (Column 1) and the moment (in time period) that most closely targets it (Columns 2 and 3). Column 4 reports the model-simulated moments, and Column 5 contains the empirical estimates with robust standard errors in parentheses. Panel A includes the within-county moments described in Section D.3.3.1, and Panel B includes the across-county moments described in D.3.3.2. Our estimation procedure, described in Section D.3.2, matches these target moments exactly, up to a preset numerical tolerance of 1%.

Table A.2. Coverage Rates

State	1850	1860	1870	1880	State	1850	1860	1870	1880
AL	✓	✓	✓	✓	MO	✓	✓	✓	✓
AZ	-	-	0%	0%	MT	-	-	✓	✓
AR	✓	✓	✓	✓	NE	-	✓	✓	✓
CA	✓	✓	✓	✓	NV	-	-	✓	✓
CO	-	-	✓	✓	NH	✓	✓	✓	✓
CT	✓	✓	✓	✓	NJ	✓	✓	✓	✓
DE	✓	✓	✓	✓	NM	-	0%	0%	✓
DC	✓	✓	✓	✓	NY	✓	✓	82%	99%
FL	✓	✓	✓	✓	NC	✓	84%	✓	✓
GA	0%	0%	0%	✓	ND & SD	-	-	0%	18%
ID	-	-	✓	✓	OH	✓	26%	74%	68%
IL	✓	✓	46%	✓	OR	✓	✓	✓	✓
IN	✓	✓	✓	✓	PA	✓	✓	✓	✓
IA	✓	✓	✓	✓	RI	✓	✓	✓	✓
KS	-	✓	✓	✓	SC	✓	✓	✓	✓
KY	✓	✓	✓	✓	TN	✓	30%	35%	✓
LA	0%	0%	0%	✓	TX	✓	✓	85%	✓
ME	✓	✓	✓	✓	UT	-	✓	✓	✓
MD	✓	✓	0%	✓	VT	✓	✓	✓	✓
MA	✓	✓	32%	✓	VA	✓	✓	✓	✓
MI	✓	✓	49%	✓	WA	-	✓	✓	✓
MN	✓	✓	✓	✓	WV	-	-	✓	✓
MS	✓	✓	✓	✓	WI	✓	✓	✓	✓

Notes: This table shows our coverage of counties. Percents indicate estimates of the share of establishments that we digitized, given the published county-level tabulations. In 1850, the Census records for three counties in California (Contra Costa, San Francisco, and Santa Clara) were lost and never tabulated, we have complete coverage of the remaining counties in California. Dashes indicate that no survey was conducted, checkmarks indicate that we have complete coverage.

Table A.3. Lumber and Flour Mill Activity in 1850, by County Waterpower Potential, by Different River Classifications

	Baseline (1)	Intermittent River (2)	12-Month Average (3)	2.75 HP Threshold (4)
Panel A. Number of Waterpowered Mills				
Lower Waterpower	-1.059	0.019	-0.557	-1.007
	(0.129)	(0.036)	(0.105)	(0.123)
Panel B. Revenue of Waterpowered Mills				
Lower Waterpower	-1.126	0.015	-0.665	-1.059
	(0.244)	(0.059)	(0.167)	(0.232)
Panel C. Steam Share of Mills				
Lower Waterpower	0.089	-0.004	0.046	0.080
	(0.015)	(0.003)	(0.015)	(0.015)
Panel D. Steam Share of Revenue				
Lower Waterpower	0.127	-0.007	0.052	0.113
	(0.022)	(0.005)	(0.023)	(0.022)
Panel E. Total Number of Mills				
Lower Waterpower	-0.960	0.014	-0.501	-0.911
	(0.119)	(0.036)	(0.094)	(0.112)
Panel F. Total Revenue of Mills				
Lower Waterpower	-0.876	-0.003	-0.472	-0.886
	(0.212)	(0.050)	(0.150)	(0.183)
# County-Industries	1,199	1,191	1,199	1,196

Notes: This table shows the relationship between 1850 milling activity and waterpower potential. "Lower Waterpower" is a negative standardized measure of county waterpower potential (as described in the text) with standard deviation of one.

Column 1 uses the benchmark measure of waterpower potential from the main text, as in Table 3 column 1 (where waterpower potential is proportional to the fall height times the average flow rate in the three lowest months in the year). Column 2 instead calculates waterpower potential only from intermittent rivers, column 3 uses the 12-month average flow rate, and column 4 only uses river segments that produce more than 2.75 horsepower per mile, which is the lowest horsepower the water census uses. "Artificial Path" rivers are not formally labeled as intermittent or not, and so we predict their classification as a function of their observables, such as their monthly flows. Each panel shows the effect of waterpower potential on a different outcome. Panel A shows total number of water powered mills and Panel B shows the total revenue of water powered mills. Panel C shows the share of mills using steam power, and Panel D shows the share of milling revenue from steam power. Panel E shows the total number of mills, and Panel F shows total milling revenue. Panels A, B, E, and F use PPML estimation. Panels C and D weight counties by their number of mills.

All regressions include industry fixed effects and our baseline controls interacted with industry: an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850; an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network.

Each observation is a county-industry in 1850. Robust standard errors clustered by county are reported in parentheses. Data from our main sample counties (Figure 5), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Table A.4. Capital Stock by Power Usage Type

	Log Capital Stock			
	All Mills		Entrants Only	
	(1)	(2)	(3)	(4)
Steam User	0.207	0.360	0.215	0.339
	(0.017)	(0.027)	(0.018)	(0.025)
Steam User ×		-0.078		-0.106
Decade		(0.011)		(0.015)
# Mills	83,082	83,082	52,878	52,878

Notes: This table compares capital stock and its relative change across decades between water-powered and steam-powered mills. Columns (1) and (2) include all mills with positive capital stock, and columns (3) and (4) restrict the sample to entrant mills. Columns (1) and (3) show the difference in average log capital stock between steam and water-powered mills. Columns (2) and (4) additionally control for the interaction of being a steam user and the decade.

All regressions control for county-industry-period fixed effects, in addition to log output. Each observation is an establishment in all columns. Robust standard errors clustered by county are reported in parentheses. Data from our digitized establishment-level Census of Manufactures, 1850–1880.

Table A.5. Survival Rates, by County Waterpower Potential and Initial Power Source

	Water Survival Rate (1)	Steam Survival Rate (2)	Difference (1) − (2) (3)
Elasticity with Respect to Lower Waterpower:			
In 1860	-0.186	-0.440	0.254
	(0.067)	(0.203)	(0.210)
# County-Industries	1,199	1,199	
In 1870	-0.237	-0.209	-0.028
	(0.063)	(0.124)	(0.131)
# County-Industries	1,199	1,199	
In 1880	-0.186	0.008	-0.195
	(0.048)	(0.069)	(0.080)
# County-Industries	1,199	1,199	

Notes: This table shows the elasticity of survival for both water and steam mills, over the previous decade, with respect to county waterpower potential. "Lower Waterpower" is a negative standardized measure of county waterpower potential, with standard deviation of one, so the estimates reflect differences in counties with one standard deviation lower waterpower potential.

Column 1 reports results for water powered incumbents, column 2 reports results for steam powered incumbents, and column 3 reports the differences. Each row corresponds to a different PPML regression, using data from the indicated Census year and previous Census year, which approximates percent differences in the rates.

All regressions include county-industry fixed effects, industry-year fixed effects, and our baseline controls interacted with industry and year: an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850; an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network.

Each observation is a county-industry-year. Robust standard errors clustered by county are reported in parentheses. Data from our main sample counties (Figure 5), using our digitized establishment-level Census of Manufactures (1860-1880) and NHDPlusV2.

Table A.6. Relative Growth of Water Users

	Log Revenue (1)
Panel A. Water Users vs. Steam Switchers	
Relative Growth of Water Users	-0.694
	(0.077)
# Establishment-Years	4,865
Panel B. Young Water Users vs. Old Water Users	
Relative Growth of Young Water Users	0.023
	(0.031)
# Establishment-Years	5,716
Panel C. Continuing Water Users vs. Water Entrants	
Relative Growth of Continuing Water Users	0.024
	(0.019)
# County-Industry-Years	2,633

Notes: This table tests for learning-by-doing among waterpowered mills. Each panel compares revenue growth (1860–1870 and 1870–1880) for water stayers—those who enter with water and continue using it—against a different comparison group. Panel A compares water stayers to water-to-steam switchers who entered in the same year. Panel B compares young water users to older water users who entered in or before the previous decade. Panel C compares the revenue growth of continuing water users relative to changes in average revenue among new water entrants.

All regressions control for county-industry-period fixed effects. Panels A and B also control for initial (log) revenue size. Each observation is an establishment-period in Panels A and B, and a county-industry-period in Panel C. Robust standard errors clustered by county are reported in parentheses. Data from our digitized establishment-level Census of Manufactures, 1860–1880.

Table A.7. Robustness to Alternative Drivers of Steam Use

	Water Mills	Steam Share	Growth in Total Mills			Steam Diffusion of Mills		
	1850	1850	1850 to 1860	1860 to 1870	1870 to 1880	1850 to 1860	1860 to 1870	1870 to 1880
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1. Baseline	-1.059	0.089	0.222	0.106	0.116	0.068	0.032	-0.010
	(0.130)	(0.015)	(0.061)	(0.052)	(0.034)	(0.017)	(0.014)	(0.014)
2. 1850 coal production controls	-1.044	0.088	0.221	0.104	0.111	0.067	0.030	-0.010
	(0.130)	(0.015)	(0.061)	(0.053)	(0.034)	(0.017)	(0.013)	(0.014)
3. Each type of coal separately	-1.059	0.089	0.223	0.107	0.115	0.068	0.032	-0.010
	(0.130)	(0.015)	(0.061)	(0.052)	(0.034)	(0.017)	(0.014)	(0.014)
4. Square and cubic in county coal shares	-1.051	0.085	0.206	0.124	0.116	0.071	0.027	-0.008
	(0.129)	(0.015)	(0.060)	(0.053)	(0.035)	(0.017)	(0.013)	(0.013)
5. FAO suitability for wheat	-1.068	0.087	0.205	0.120	0.127	0.066	0.031	-0.012
	(0.130)	(0.015)	(0.060)	(0.053)	(0.034)	(0.017)	(0.014)	(0.013)
6. Woodland share in county	-1.007	0.093	0.182	0.092	0.109	0.059	0.028	-0.019
	(0.131)	(0.015)	(0.065)	(0.054)	(0.035)	(0.017)	(0.014)	(0.014)
7. 1850 local MFG wages	-1.064	0.094	0.280	0.077	0.097	0.041	0.053	-0.015
	(0.155)	(0.017)	(0.069)	(0.063)	(0.039)	(0.018)	(0.016)	(0.015)
8. 1850 engineers and mechanics	-1.066	0.091	0.218	0.108	0.119	0.071	0.028	-0.008
	(0.129)	(0.015)	(0.062)	(0.053)	(0.034)	(0.017)	(0.013)	(0.014)
9. 1850 access to banks	-1.048	0.085	0.221	0.109	0.115	0.068	0.032	-0.010
	(0.129)	(0.015)	(0.062)	(0.052)	(0.034)	(0.017)	(0.013)	(0.014)
10. All controls	-0.976	0.083	0.220	0.102	0.099	0.037	0.040	-0.017
	(0.137)	(0.017)	(0.070)	(0.068)	(0.040)	(0.018)	(0.015)	(0.017)

Notes: This table shows the robustness of the relationship between waterpower potential and the number of 1850 water establishments, the 1850 steam share, and mill growth from 1850-1880. This table focuses on additional controls for alternative factors which may have driven steam adoption, as described in Appendix C.2.

All regressions include industry-year fixed effects, and our baseline controls interacted with industry and year. All regressions other than those reported in Columns 1 and 2 additionally include county-industry fixed effects. Our baseline controls are an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850; an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network.

Each observation is a county-industry-year. Robust standard errors clustered by county are reported in parentheses. Data from our main sample counties (Figure 5), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Table A.8. Robustness to Alternative Drivers of County Growth

	Water Mills	Steam Share	Growth in Total Mills			Steam Diffusion of Mills		
	1850	1850	1850 to 1860	1860 to 1870	1870 to 1880	1850 to 1860	1860 to 1870	1870 to 1880
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1. Baseline	-1.059	0.089	0.222	0.106	0.116	0.068	0.032	-0.010
	(0.130)	(0.015)	(0.061)	(0.052)	(0.034)	(0.017)	(0.014)	(0.014)
2. No controls for MA/navigable rivers	-1.256	0.077	0.294	0.112	0.125	0.085	0.033	-0.013
	(0.135)	(0.015)	(0.062)	(0.051)	(0.034)	(0.017)	(0.013)	(0.014)
3. No controls for coal	-1.063	0.095	0.239	0.104	0.121	0.081	0.036	-0.006
	(0.125)	(0.016)	(0.063)	(0.052)	(0.034)	(0.019)	(0.013)	(0.015)
4. No extra controls	-1.272	0.080	0.310	0.115	0.137	0.090	0.033	-0.014
	(0.131)	(0.015)	(0.063)	(0.050)	(0.033)	(0.019)	(0.013)	(0.015)
5. Time-varying market access	-1.054	0.088	0.214	0.108	0.123	0.067	0.033	-0.009
	(0.126)	(0.015)	(0.059)	(0.052)	(0.033)	(0.017)	(0.013)	(0.013)
6. Time-varying population	-0.766	0.090	0.150	0.094	0.094	0.054	0.021	-0.018
	(0.108)	(0.015)	(0.064)	(0.057)	(0.036)	(0.017)	(0.013)	(0.014)
7. 1850 population	-0.817	0.094	0.179	0.105	0.103	0.057	0.029	-0.011
	(0.115)	(0.016)	(0.061)	(0.054)	(0.034)	(0.017)	(0.014)	(0.014)
8. Appalachia	-1.043	0.088	0.222	0.107	0.115	0.067	0.032	-0.011
	(0.130)	(0.015)	(0.061)	(0.052)	(0.034)	(0.017)	(0.014)	(0.014)
9. Frontier	-1.054	0.089	0.217	0.103	0.119	0.068	0.032	-0.010
	(0.130)	(0.015)	(0.061)	(0.052)	(0.034)	(0.017)	(0.014)	(0.014)
10. 1850 agricultural share	-1.045	0.093	0.209	0.096	0.106	0.066	0.030	-0.013
	(0.128)	(0.015)	(0.062)	(0.053)	(0.033)	(0.017)	(0.013)	(0.013)
11. Portage sites	-1.066	0.091	0.221	0.106	0.116	0.070	0.029	-0.010
	(0.129)	(0.015)	(0.061)	(0.052)	(0.034)	(0.017)	(0.013)	(0.014)
12. Civil war controls	-0.921	0.086	0.225	0.119	0.074	0.061	0.028	-0.011
	(0.122)	(0.015)	(0.063)	(0.055)	(0.035)	(0.017)	(0.013)	(0.014)
13. Time-invariant controls from rows 8-12	-0.914	0.091	0.216	0.100	0.075	0.063	0.029	-0.009
	(0.121)	(0.015)	(0.063)	(0.054)	(0.034)	(0.017)	(0.013)	(0.014)
14. All time-invariant controls (rows 7-12)	-0.670	0.092	0.184	0.114	0.070	0.056	0.027	-0.007
	(0.101)	(0.016)	(0.063)	(0.056)	(0.035)	(0.017)	(0.013)	(0.014)

Notes: This table shows the robustness of the relationship between waterpower potential and the number of 1850 water establishments, the 1850 steam share, and growth 1850-1880. This table focuses on additional controls for alternative factors which may have driven county growth, as described in Appendix C.2.

Unless otherwise specified (in rows 2-5), all regressions include industry-year fixed effects, and our baseline controls interacted with industry and year. All regressions other than those reported in Columns 1 and 2 additionally include county-industry fixed effects. Our baseline controls are an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850; an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network.

Each observation is a county-industry-year. Robust standard errors clustered by county are reported in parentheses. Data from our main sample counties (Figure 5), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Table A.9. Per Capita Manufacturing Growth and Steam Adoption by Waterpower Potential

	Population (1)	Mills Per Capita (2)	Mill Revenue Per Capita (3)
Panel A. Differences in Lower Waterpower Counties:			
In 1850	-0.286	-0.674	-0.595
	(0.226)	(0.233)	(0.232)
Panel B. Growth in Lower Waterpower Counties:			
From 1850 to 1860	0.094	0.128	0.116
	(0.029)	(0.064)	(0.082)
From 1860 to 1870	0.067	0.040	0.113
	(0.040)	(0.060)	(0.066)
From 1870 to 1880	0.075	0.041	0.089
	(0.024)	(0.043)	(0.097)
# County-Industries		1,199	1,199

Notes: This table shows the relationship between per capita growth in mill activity and county waterpower potential. "Lower Waterpower" is a negative standardized measure of county waterpower potential, with standard deviation of one, so the estimates reflect differences in counties with one standard deviation lower waterpower potential.

The outcome in column 1 is (log) population, the outcome in column 2 is mills per capita, and the outcome in column 3 is milling revenue per capita. Panel A reports cross-sectional differences in 1850. Panel B reports growth rates over the following decades. Each row corresponds to a different regression, using only data from the indicated years. Column 1 reports OLS estimates, and columns 2-3 report PPML estimates, which approximate percent differences.

All regressions include our baseline controls: an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850; an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network.

Each observation is a county-year. Robust standard errors clustered by county are reported in parentheses. Data from our main sample counties (Figure 5), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Table A.10. Steam Use, by Distance to Railroad Station

	From Entrants (1)	From Water Incumbents (2)	Difference (1) − (2) (3)
Lower Waterpower	0.175	0.045	0.131
	(0.021)	(0.014)	(0.017)
Log Distance, WPP-to-RR Station	0.018	-0.026	0.044
	(0.041)	(0.028)	(0.041)
Log Distance, to RR Station	-0.019	0.026	-0.045
	(0.046)	(0.032)	(0.045)
# County-Industries	1,192	841	

Notes: This table shows the relationship between waterpower potential, railroad station placement, and the steam use of entrant and incumbent mills from 1860-1880. "Lower Waterpower" is a negative standardized measure of county waterpower potential, with standard deviation of one, so the estimates reflect differences in counties with one standard deviation lower waterpower potential. "Log Distance, WPP-to-RR Station" is the log of the average distance from water segments to their closest railroad station, weighting by potential horsepower. "Log Distance, to RR Station" is the log of the average distance from all points in the county to their closest railroad station.

The outcome in column 1 is the share of entrants using steam power, the outcome in column 2 is the share of water incumbents (incumbents who used water power in the previous decade) who switched to steam power, and column 3 reports the difference. Each row corresponds to different OLS regressions, using data pooled across all 1860-1880. The sample is restricted to all county-industry-years at least one current entrant (in column 1) or incumbent (in column 2).

All regressions include our baseline controls interacted with year and industry: an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850; an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network. Regressions are weighted by the number of mills in the county in 1850.

Each observation is a county-industry-year. Robust standard errors clustered by county are reported in parentheses. Data from our main sample counties (Figure 5), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Table A.11. Robustness to Sample

	Water Mills	Steam Share	Growth in Total Mills			Steam Diffusion of Mills		
	1850	1850	1850 to 1860	1860 to 1870	1870 to 1880	1850 to 1860	1860 to 1870	1870 to 1880
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1. Baseline	-1.059	0.089	0.222	0.106	0.116	0.068	0.032	-0.010
	(0.130)	(0.015)	(0.061)	(0.052)	(0.034)	(0.017)	(0.014)	(0.014)
2. Include extensive margin of counties	-1.149	0.088	0.294	0.090	0.135	0.071	0.031	-0.010
	(0.132)	(0.015)	(0.062)	(0.051)	(0.033)	(0.017)	(0.013)	(0.014)
3. At least 3 mills in 1850	-0.942	0.081	0.167	0.104	0.108	0.070	0.034	-0.011
	(0.133)	(0.016)	(0.063)	(0.057)	(0.039)	(0.017)	(0.014)	(0.014)
4. At least 5 mills in 1850	-0.869	0.075	0.130	0.107	0.090	0.066	0.045	-0.015
	(0.135)	(0.017)	(0.069)	(0.063)	(0.042)	(0.018)	(0.014)	(0.015)
5. Exclude large grouped counties	-1.108	0.098	0.230	0.103	0.116	0.072	0.028	-0.010
	(0.129)	(0.015)	(0.062)	(0.053)	(0.034)	(0.017)	(0.013)	(0.014)
6. Exclude top and bottom 1% WPP counties	-1.164	0.088	0.240	0.117	0.136	0.073	0.034	-0.011
	(0.126)	(0.016)	(0.064)	(0.056)	(0.036)	(0.017)	(0.014)	(0.014)
7. Exclude top and bottom 5% WPP counties	-1.138	0.087	0.242	0.110	0.122	0.061	0.035	-0.017
	(0.145)	(0.019)	(0.074)	(0.063)	(0.042)	(0.020)	(0.016)	(0.016)
8. Exclude largest 20 cities in 1850-1880	-1.052	0.088	0.226	0.097	0.120	0.073	0.035	-0.013
	(0.130)	(0.014)	(0.063)	(0.055)	(0.037)	(0.017)	(0.013)	(0.014)
9. Exclude merchant mill cities	-1.016	0.092	0.213	0.097	0.117	0.066	0.032	-0.010
	(0.126)	(0.015)	(0.064)	(0.055)	(0.036)	(0.018)	(0.015)	(0.014)

Notes: This table shows the robustness of the relationship between waterpower potential and the number of 1850 water establishments, the 1850 steam share, and growth 1850-1880. This table focuses on alternative choices for the sample of counties in the analysis, as described in Appendix C.2.

All regressions include industry-year fixed effects, and our baseline controls interacted with industry and year. All regressions other than those reported in Columns (1) and (2) additionally include county-industry fixed effects. Our baseline controls are an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850; an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network.

Each observation is a county-industry-year. Robust standard errors clustered by county are reported in parentheses. Except for the stated modifications in each row, data from our main sample counties (Figure 5), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Table A.12. Confusion Matrix: Hand Links vs. Predicted Links

	Machine Learning Links			
	Linked (Same)	Linked (Different)	Not Linked	Total
Hand Links	(1)	(2)	(3)	(4)
Panel A. 1850 to 1860				
Linked	2,954	117	543	3,614
Not Linked	-	454	13,878	14,332
Panel B. 1860 to 1870				
Linked	2,763	149	459	3,371
Not Linked	-	388	13,798	14,186
Panel C. 1870 to 1880				
Linked	4,050	161	1,293	5,504
Not Linked	-	540	17,200	17,740

Notes: This table shows the confusion matrix for the panel links. The rows report matches made by the hand-linking procedure, and the columns correspond to matches made by the machine-learning model, both of which are described in Appendix A.2.1. Data from our main sample counties (Figure 5), using our digitized establishment-level Census of Manufactures (1850-1880).

Table A.13. Robustness to Measurement and Linking Error: Entry and Survival

	Entry Rate			Survival Rate		
	1850 to 1860	1860 to 1870	1870 to 1880	1850 to 1860	1860 to 1870	1870 to 1880
	(1)	(2)	(3)	(4)	(5)	(6)
1. Baseline	0.316	0.159	0.185	-0.227	-0.289	-0.158
	(0.072)	(0.058)	(0.042)	(0.066)	(0.060)	(0.041)
2. Links that are both ML and hand-linked	0.294	0.148	0.167	-0.199	-0.275	-0.165
	(0.070)	(0.057)	(0.040)	(0.072)	(0.062)	(0.043)
3. Only ML links	0.324	0.157	0.176	-0.262	-0.270	-0.163
	(0.072)	(0.058)	(0.041)	(0.073)	(0.058)	(0.040)
4. Raising ML linking threshold to 0.6	0.281	0.144	0.157	-0.183	-0.299	-0.193
	(0.068)	(0.057)	(0.039)	(0.078)	(0.066)	(0.050)
5. Lowering ML linking threshold to 0.2	0.349	0.172	0.199	-0.204	-0.133	-0.100
	(0.075)	(0.062)	(0.045)	(0.060)	(0.046)	(0.033)
6. Only business-name mills	0.319	0.238	0.148	-0.257	-0.254	-0.155
	(0.070)	(0.059)	(0.048)	(0.082)	(0.081)	(0.058)
7. Only non-business name mills	0.269	0.038	0.209	-0.212	-0.316	-0.255
	(0.082)	(0.073)	(0.048)	(0.096)	(0.087)	(0.063)
8. Only mills with all positive inputs	0.343	0.194	0.172	-0.207	-0.269	-0.122
	(0.079)	(0.061)	(0.044)	(0.067)	(0.063)	(0.043)
9. Include inactive mills with zero output	0.316	0.169	0.178	-0.244	-0.295	-0.156
	(0.071)	(0.058)	(0.042)	(0.066)	(0.059)	(0.040)
10. Include mills using manual/other power	0.317	0.159	0.180	-0.213	-0.253	-0.148
	(0.072)	(0.058)	(0.042)	(0.065)	(0.059)	(0.041)

Notes: This table shows the robustness of the measured elasticity of mill entry and mill survival, over the previous decade, with respect to county water power potential. This table focuses on linking and measurement error, as described in Appendix C.2.

All regressions include county-industry fixed effects and our baseline controls interacted with industry: an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850; an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network.

Each observation is a county-industry-year. Robust standard errors clustered by county are reported in parentheses. Data from our main sample counties (Figure 5), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Table A.14. Robustness to Measurement and Linking Error: Steam Use

	Entrant Steam Share			Incumbent Steam Share		
	1860	1870	1880	1860	1870	1880
	(1)	(2)	(3)	(4)	(5)	(6)
1. Baseline	0.164	0.186	0.168	0.035	0.051	0.053
	(0.024)	(0.022)	(0.022)	(0.022)	(0.018)	(0.024)
2. Links that are both ML and hand-linked	0.164	0.185	0.166	0.022	0.049	0.043
	(0.024)	(0.022)	(0.021)	(0.021)	(0.017)	(0.025)
3. Only ML links	0.167	0.187	0.165	0.029	0.051	0.044
	(0.024)	(0.022)	(0.022)	(0.023)	(0.019)	(0.024)
4. Raising ML linking threshold to 0.6	0.163	0.186	0.167	0.035	0.039	0.052
	(0.023)	(0.022)	(0.021)	(0.024)	(0.019)	(0.026)
5. Lowering ML linking threshold to 0.2	0.163	0.188	0.172	0.052	0.077	0.055
	(0.024)	(0.022)	(0.022)	(0.020)	(0.024)	(0.025)
6. Only business-name mills	0.163	0.173	0.158	0.028	0.066	0.062
	(0.026)	(0.025)	(0.024)	(0.032)	(0.036)	(0.033)
7. Only non-business name mills	0.145	0.175	0.162	0.025	0.023	0.058
	(0.029)	(0.022)	(0.024)	(0.022)	(0.023)	(0.031)
8. Only mills with all positive inputs	0.162	0.185	0.164	0.030	0.047	0.059
	(0.024)	(0.023)	(0.022)	(0.024)	(0.018)	(0.026)
9. Include inactive mills with zero output	0.164	0.188	0.168	0.036	0.053	0.048
	(0.024)	(0.021)	(0.021)	(0.022)	(0.018)	(0.024)
10. Include mills using manual/other power	0.163	0.186	0.168	0.035	0.051	0.053
	(0.024)	(0.022)	(0.022)	(0.022)	(0.017)	(0.024)

Notes: This table shows the robustness of the relationship between waterpower potential and the share of entrants and water incumbents using steam. This table focuses on linking and measurement error, as described in Appendix C.2.

All regressions include county-industry fixed effects and our baseline controls interacted with industry: an indicator for the presence of navigable waterways in the county; distance to the nearest navigable waterway; county market access in 1850; an indicator for workable coal deposits in the county; the share of the county covered by coal deposits; and access to coal via the transportation network.

Each observation is a county-industry-year. Robust standard errors clustered by county are reported in parentheses. Data from our main sample counties (Figure 5), using our digitized establishment-level Census of Manufactures (1850-1880) and NHDPlusV2.

Table A.15. Standard Errors on Structural Parameters

Parameter	Description	Value	Standard Error
$\tilde{c}_S^{(initial)}$	Steam cost differential (initial)	0.239	0.038
$\tilde{c}_S^{(terminal)}$	Steam cost differential (terminal)	-0.086	0.008
$c(W,S)$	Residual switching costs from water	0.014	0.038
$c(S,W)$	Residual switching costs from steam	0.055	0.052
f_e^W	Operating cost of water entrant	0.433	0.167
f_o^W	Operating cost of water user	0.107	0.023
$\tilde{c}_L(W)$	Water cost differential in lower-water-power county	0.038	0.011
η	Elasticity of local demand	5.900	0.012
κ	Agglomeration in steam adoption	0.016	0.092
α	Agglomeration in steam production	0.025	0.008

Notes: This table shows the point estimates and standard errors for the parameters estimated using our Newton–based estimation procedure. See Section D.3.4 for details. All parameters except η and α_S are measured in percentage of 1850 median firm sales.

Table A.16. Jacobian: Effect of Parameter on Moments, $\frac{dM}{d\theta_k}$

	$\tilde{c}_S^{(initial)}$ (1)	$\tilde{c}_S^{(terminal)}$ (2)	$c(W,S)$ (3)	$c(S,W)$ (4)	f_e^W (5)	f_o^W (6)	$\tilde{c}_L(W)$ (7)	η (8)	κ (9)	α (10)
Steam Share 1850	**-0.50**	-0.55	-0.27	-0.03	0.80	13.70	0.00	0.19	-0.12	2.08
Steam Share 1880	-0.38	**-2.12**	-0.33	0.47	0.78	16.10	0.00	0.14	-0.88	11.39
Water Use: W-Inc – Ent	0.53	0.62	**7.03**	0.00	2.38	-19.73	0.00	0.23	-0.10	-12.40
Steam Use: S-Inc – Ent	1.25	4.62	0.38	**10.53**	3.35	30.25	0.00	-0.20	1.62	12.12
Firm Size: Inc – Ent	-0.40	-1.27	-0.75	0.33	**-0.47**	12.80	0.00	0.51	-0.53	5.12
Water Exit	-0.12	-0.30	-0.20	0.03	-0.07	**4.10**	0.00	0.00	-0.10	1.72
Steam Share: L – B	-0.35	-0.38	0.00	0.07	0.15	4.47	**2.83**	0.25	-0.22	4.14
Output: L – B	-1.55	-3.43	0.70	0.60	2.30	41.33	-7.30	**-17.07**	-2.55	50.91
Steam Share Growth: L – B	0.33	0.25	0.45	-0.10	-0.33	-7.15	0.53	-0.25	**-0.22**	-2.13
Output Growth: L – B	0.80	-0.47	1.40	0.15	-1.12	-17.27	9.03	10.55	-2.57	**13.05**

Notes: This table shows the Jacobian of the moment function, capturing how simulated moments (in the rows) change with parameter values (in the columns). "WI – E" denotes differences between water incumbents and entrants, "SI – E" denotes differences between steam incumbents and entrants, and "L – B" denotes differences between the lower water power and baseline regions. We order the table rows and columns such that the diagonal elements (in bold font) capture the relationship between parameters and their target moments, as discussed in Sections D.3.3.1-D.3.3.2. The table includes the moment-parameter pairs of our Newton-based estimation in Table A.1. The Jacobian matrix contains the local derivatives of simulated moments with respect to parameter values, evaluated numerically around our baseline parameter estimates. All parameters except η and α_S are measured in percent of 1850 median firm sales.

Table A.17. Sensitivity: Effect of Moment on Parameters, $\frac{d\theta}{dM_k}$

	Steam Share 1850	Steam Share 1880	Water Use: WI – E	Steam Use: SI – E	Firm Size: I – E	Water Exit	Steam Share: L – B	Output: L – B	Steam Share Growth: L – B	Output Growth: L – B
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\tilde{c}_S^{(initial)}$	**-0.52**	1.23	-0.07	0.07	-4.25	16.38	-0.77	-0.23	2.45	-0.09
$\tilde{c}_S^{(terminal)}$	0.78	**-0.76**	-0.06	0.03	-0.01	-0.03	-0.29	0.10	0.04	0.17
$c(W,S)$	-0.34	-0.19	**0.20**	0.00	-0.29	3.24	0.00	0.01	-0.28	0.02
$c(S,W)$	-0.19	-0.00	0.02	**0.06**	1.49	-5.35	0.24	0.01	-0.18	-0.05
f_e^W	0.62	0.46	-0.08	0.00	**-0.25**	-3.19	-0.02	-0.01	0.15	-0.01
f_o^W	0.04	-0.01	0.00	0.00	-0.14	**0.83**	-0.03	-0.01	0.10	-0.00
$\tilde{c}_L(W)$	-0.02	0.08	-0.01	0.01	-0.26	0.84	**0.32**	-0.03	0.33	-0.03
η	-0.01	-0.03	0.02	-0.00	0.01	0.05	-0.17	**-0.01**	-0.42	0.07
κ	-1.77	0.50	0.13	0.00	-2.01	8.34	0.47	-0.15	**-1.61**	-0.17
α	-0.12	0.01	0.00	0.00	-0.15	0.54	-0.01	0.01	-0.18	**0.02**

Notes: This table shows the sensitivity measure of Andrews, Gentzkow and Shapiro (2017), capturing how parameter estimates (in the rows) change with moment values (in the columns). "WI – E" denotes differences between water incumbents and entrants, "SI – E" denotes differences between steam incumbents and entrants, and "L – B" denotes differences between the lower water power and baseline regions. We order the table rows and columns such that the diagonal elements (in bold font) capture the relationships between parameters and target moments discussed in Sections D.3.3.1-D.3.3.2. The table includes the moment-parameter pairs of our Newton-based estimation in Table A.1. The sensitivity matrix M is related to the Jacobian J in Table A.16 as follows: $M = (J'IJ)^{-1}J'I$, where I is the identity matrix. All parameters except η and α_S are measured in percent of 1850 median firm sales.

Table A.18. Non-Targeted Differences between Lower Waterpower and Baseline Regions

Moment	Years	Model	Data
Panel A. Steam Adoption and Mill Growth (Table 4)			
Change in Steam Share of Mills	1850–1860	0.053	0.068
			(0.017)
Change in Steam Share of Mills	1860–1870	0.029	0.032
			(0.014)
Change in Steam Share of Mills	1870–1880	0.007	-0.010
			(0.014)
Total Mills	1850–1860	0.198	0.222
			(0.061)
Total Mills	1860–1870	0.166	0.106
			(0.052)
Total Mills	1870–1880	0.149	0.116
			(0.034)
Total Revenue	1850–1860	0.231	0.210
			(0.080)
Total Revenue	1860–1870	0.177	0.180
			(0.097)
Total Revenue	1870–1880	0.146	0.164
			(0.083)
Panel B. Entry Rates and Survival Rates (Table 5)			
Entry rate	1850–1860	0.232	0.328
			(0.074)
Entry rate	1860–1870	0.198	0.161
			(0.059)
Entry rate	1870–1880	0.178	0.189
			(0.043)
Survival rate	1850–1860	-0.052	-0.237
			(0.065)
Survival rate	1860–1870	-0.106	-0.276
			(0.058)
Survival rate	1870–1880	-0.127	-0.156
			(0.040)
Panel C. Steam Adoption of Entrants and Water Incumbents (Table 6)			
From Entrants	1850–1860	0.142	0.166
			(0.024)
From Entrants	1860–1870	0.169	0.187
			(0.022)
From Entrants	1870–1880	0.176	0.171
			(0.022)
From Water Incumbents	1850–1860	0.072	0.034
			(0.022)
From Water Incumbents	1860–1870	0.095	0.051
			(0.018)
From Water Incumbents	1870–1880	0.095	0.047
			(0.024)

Notes: This table replicates non-targeted regressions from Section III.B on our model-simulated data. Each panel reports the regression estimates from a different table. Columns 1 and 2 describe each regression moment, Column 3 reports the model-simulated values, and Column 4 repeats the empirical values from the relevant table in Section III.B with standard errors in parentheses.

Table A.19. Model Fit without Agglomeration

Parameter	Moment	Years	Model $\alpha_S = 0$	Model $\kappa = 0$	Data
Panel A. Baseline County					
$c(W, S)$	Water Choice Differential: Water Incumbents vs. Entrants	1850–1880	0.524	0.531	0.529 (0.061)
$c(S, W)$	Steam Choice Differential: Steam Incumbents vs. Entrants	1850–1880	1.024	1.017	1.020 (0.132)
$c_S^{(initial)}$	Steam Adoption Rate	1850	0.101	0.102	0.103 (0.006)
$c_S^{(terminal)}$	Steam Adoption Rate	1880	0.395	0.394	0.396 (0.011)
f_e	Entry Rate	1850–1860	0.750	0.750	0.750 (0.006)
f_o^E	Log Sales Differential: Incumbents vs. Entrants	1850–1880	0.131	0.130	0.129 (0.015)
f_o^W	Water Exit Rate	1850–1880	0.791	0.791	0.791 (0.003)
f_o^S	Steam Exit Rate	1850–1880	0.835	0.835	0.835 (0.006)
γ	Log Sales Differential: Steam vs. Water Users	1850–1880	0.835	0.844	0.836 (0.030)
π	Log Sales Autocorrelation	1850–1860	0.409	0.409	0.410 (0.019)
σ	Log Sales Standard Deviation	1850–1860	1.020	1.020	1.020 (0.011)
Panel B. Differences in Lower Waterpower Counties					
$c_L(W)$	Steam Adoption Rate	1850	0.087	0.087	0.087 (0.016)
η	Log Total Output	1850	-0.887	-0.885	-0.881 (0.215)
κ	Change in Steam Adoption Rate	1850, 1880	0.091	0.095	0.090 (0.019)
α	Growth of Output	1850, 1880	0.218	0.556	0.554 (0.114)

Notes: This table shows the empirical fit of our estimated model, without agglomeration in steam power. The table shows each estimated parameter of the model (Column 1) and the moment that most closely targets it (Columns 2 and 3). Columns 4 and 5 show the model-simulated moments without agglomeration in steam productivity ($\alpha_S = 0$) and steam adoption costs ($\kappa = 0$), respectively. The columns restrict each parameter to zero and exclude the corresponding target moment from the estimation. Column 6 presents the empirical estimates with robust standard errors, clustered by county, in parentheses.

Table A.20. The Impact of Steam on Mill Revenue 1830-1900 (PDV in %)

	Baseline (1)	Lower Waterpower (2)	No Water Lock-In (3)	Full Water Lock-In (4)
Total	118.70	231.78	345.40	72.90
Incumbents	0.18	0.29	0.98	-0.07
Entrants	143.82	263.72	378.61	92.21

Notes: This table reports the impact of steam on the present discounted values of mill revenues of incumbent and entrant establishments. Incumbents refer to establishments that have been active since 1829 or earlier. Entrants refer to the establishments that entered the region in 1830 or later. Incumbents represent 29% of revenues in the initial steady state without steam power. Columns (1)-(4) report the impact of steam power (measured in percent) relative to this initial steady state. Column 1 considers our baseline region, while Column 2 considers an economy with one standard deviation lower waterpower potential. Column 3 considers a counterfactual without switching barriers ($\omega^W = 1, c(W,S) = 0$). Column 4 considers a counterfactual with prohibitive switching barriers ($c(W,S) \to \infty$).

Table A.21. The Impact of Steam Power on Firm Values in 1830 (in Percentage Points)

	Baseline (1)	Lower Water Power (2)	No Water Lock-In (3)	Full Water Lock-In (4)
Total	-0.00	-0.01	0.03	-0.01
Operating Profits	-0.82	-1.29	-3.56	-0.49
Option Value of Exit	0.73	1.15	2.39	0.48
Option Value of Steam	0.09	0.13	1.21	0

Notes: This table decomposes the percent impact of steam power on firm values in 1830. "Option Value of Steam" reflects the difference in firm value relative to a mill that cannot access steam power. "Option Value of Exit" reflects the additional difference in firm value relative to a water mill that is forced to stay in business indefinitely (labeled "Operating Profits"). Appendix D.4.2.1 provides formal definitions of these components. Column 1 considers our baseline region, and Column 2 considers an economy with one standard deviation lower waterpower potential. Column 3 considers a counterfactual without switching barriers ($\omega^W = 1, c(W,S) = 0$). Column 4 considers a counterfactual with prohibitive switching barriers ($c(W,S) \to \infty$).